PAEDIATRIC ORTHOPAEDIC FRACTURE HEALING PREDICTION SYSTEM

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PAEDIATRIC ORTHOPAEDIC FRACTURE HEALING PREDICTION SYSTEM

ABSTRACT

Machine learning methods have been used in this study to analyze and predict the required healing time among paediatric orthopaedic patients. To our best knowledge, there is no study reported using machine learning methods to predict paediatric orthopaedic fracture healing time. In this study, we examined the fracture healing time in children using Random forest (RF), Self-Organizing Feature map (SOM) and support vector regression (SVR) The study sample was obtained from the paediatric orthopaedic unit at University Malaya Medical Centre, radiographs of the upper limb and lower limb fractures from children under twelve years, with ages recorded from the date and time of initial injury. Inputs assessment extracted from radiographic images included the following features: type of fracture, angulation of the fracture, the contact area percentage of the fracture, age, gender, bone type, type of fracture, and the number of bones involved. all of which were determined from the radiographic images. RF and SVR were used to select variables affecting bone healing time. Then, SOM was applied for analysis of the relationship between the selected variables with fracture healing time. Findings from this study identified fracture angulation and distance, age and bone part as important variables in explaining the fracture healing pattern. Root mean square error (RMSE) was used as a performance measure and SOM was used in this study for visualization and ordination of factors associated with healing time. Based on the outcomes obtained from the models it is concluded that SVR and SOM techniques can be used to assist in the analysis of the healing time efficiently especially in paediatric cases as it can additionally signal a non-unintentional injury or abnormal restoration, that affect the time required for bone fracture healing. Predicting healing time can be used as a tool in the treatment process for general practitioners and medical officers and in the follow-up period. We also have developed decision support using the AO trauma guide to determine the type of fracture and its management. The system prototype is available at kidsfractureexpert.com/.

Keywords: Paediatric Orthopaedic; Machine Learning; Expert System; Health Informatics.

SISTEM RAMALAN PENYEMBUHAN TULANG PATAH ORTOPEDIK PEDIATRIK

ABSTRAK

Kaedah pembelajaran mesin telah digunakan dalam kajian ini untuk menganalisis dan meramalkan masa penyembuhan yang diperlukan dalam kalangan pesakit ortopedik pediatrik. Untuk pengetahuan terbaik kami, tiada kajian yang dilaporkan menggunakan kaedah pembelajaran mesin untuk meramalkan masa penyembuhan patah tulang ortopedik kanak-kanak. Dalam kajian ini, kami mengkaji masa penyembuhan patah tulang pada kanak-kanak menggunakan Random forest (RF), Self-Organizing Feature map (SOM) dan regresi vektor sokongan (SVR) Sampel kajian diperolehi daripada unit ortopedik pediatrik di Pusat Perubatan Universiti Malaya, radiografi bahagian atas dan bahagian bawah patah tulang daripada kanak-kanak di bawah dua belas tahun, dengan umur direkodkan dari tarikh dan masa kecederaan awal. Penilaian input yang diekstrak daripada imej radiografi termasuk ciri berikut: jenis patah tulang, angulasi patah, peratusan kawasan sentuhan patah tulang, umur, jantina, jenis tulang, jenis patah tulang dan bilangan tulang yang terlibat. semuanya ditentukan daripada imej radiografik. RF dan SVR digunakan untuk memilih pembolehubah yang mempengaruhi masa penyembuhan tulang. Kemudian, SOM digunakan untuk analisis hubungan antara pembolehubah yang dipilih dengan masa penyembuhan patah tulang. Dapatan daripada kajian ini mengenal pasti angulasi patah dan jarak, umur dan bahagian tulang sebagai pembolehubah penting dalam menjelaskan corak penyembuhan patah. Ralat min kuasa dua akar (RMSE) digunakan sebagai ukuran prestasi dan SOM digunakan dalam kajian ini untuk visualisasi dan pentahbisan faktor yang berkaitan dengan masa penyembuhan. Berdasarkan hasil yang diperoleh daripada model tersebut, disimpulkan bahawa teknik SVR dan SOM boleh digunakan untuk membantu dalam analisis masa penyembuhan dengan cekap terutamanya dalam kes pediatrik kerana ia boleh memberi isyarat tambahan kepada kecederaan yang tidak disengajakan atau pemulihan yang tidak normal, yang menjejaskan masa yang diperlukan untuk penyembuhan patah tulang. Meramal masa penyembuhan boleh digunakan sebagai alat dalam proses rawatan untuk pengamal am dan pegawai perubatan dan dalam tempoh susulan. Kami juga telah membangunkan sokongan keputusan menggunakan panduan trauma AO untuk menentukan jenis patah tulang dan pengurusannya. Prototaip sistem tersedia di kidsfractureexpert.com/.

Kata Kunci: Ortopedik Pediatrik; Pembelajaran Mesin; Sistem Pakar; Informatik Kesihatan.

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My grandparents, my family members, my friends, and my special companions have helped me in every way. Thank you for providing a listening ear whenever things seemed difficult to manage. Without their love and endless encouragement, this thesis will not be the way it is today.

Finally, I acknowledge with deep gratitude and appreciation to this beautiful world where I have the opportunity to explore and learn. I believe that life is full of mystery and excitement, there is storm besides sunshine and rainbow. Dancing in the

rain is an art of living. Although it can be disappointing to find that society today is gradually forgetting the meaning of life where they tend to live by the imitation of others. I believe that there is still hope and therefore, I thank myself for living and believing, with Rock n' Roll as my spiritual strength to live and to make the world a better place.

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LIST OF SYMBOLS AND ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
AUROC	Area Under Receiver Operating Curve
DFD	Data Flow Diagram
ER	Entity Relation
HTML	Hypertext Markup Language
ML	Machine Learning
MLP	Multiple Layer Perceptron
MSE	Mean Square Error
OOB	Out of Bag
OPAD	Osteoporosis Advisor
PCCF	The AO Paediatric Comprehensive Classification of Long-Bone Fracture
PK	Primary Key
RF	Random Forest
RMSE	Root Mean Square Error
ROC	Receiver Operating Curve
SD	Standard Deviation
SOM	Self-Organizing Map
SUS	System Usability Scale
SVM	Support Vector Machine
SVR	Support Vector Regression
XGB	Extreme Gradient Boosting

CHAPTER 1 - INTRODUCTION

1.1 Overview

The objective of this study is to create a machine learning model for predicting the healing rate of bone fracture patients in paediatrics. We developed a system prototype that incorporates a machine learning algorithm with the highest performance that we will able to provide assistant and guidance to medical practitioners in presence of a paediatric fracture. The prototype also includes an expert system using if-then rules based on the AO trauma guide to fine out the fracture type and its aftercare.The inspiration of the research is primarily due to the limited literature reported on machine learning application on healing rate prediction for bone fracture, especially among paediatric patients. The developed web-based system enables a user to enter the patients' information to predict the healing rate of the bone fracture among children, at the same time the system can provide suggestions on the type of fracture and patients aftercare. The developed system also consists of a basic patient management system and medical personnel management system that allows user to view, update and delete patient information. The system prototype is available at kidsfractureexpert.com/.

1.2 Background Study

A fracture is a medical condition in which the bone's continuity is disrupted (Nordqvist, Petersson, & Redlund-Johnell, 1998) affecting the bone's cortex. When a physical force is being applied upon a bone that is stronger than the bone itself and it may lead to a bone fracture incidence (Davis, 2020). Adult fractures differ significantly from children's fractures (0 to 12 years old).

Firstly, a fracture occurred in a child would take half of the time as compare to adult for full recovery for the corresponding fracture (Ogden, 2000), depending on the child's age and fracture type. A child may take half of the time a teen usually takes to heal the same fracture type (Gupta, Alderliesten, & Benedictus, 2015). The reason children's fracture patterns differ from the adult is that children's bones are more elastic. (Nordqvist, Petersson, & Redlund-Johnell, 1998). (Budd, 2012) stated that because children's bone structure and biomechanics are different from adult bones, they will have different fracture patterns, healing mechanisms, and management compared to adults' fractures.

According to (Renee, 2016), although children's fractures are generally less complicated than adults, fracture cases are more common in children rather than in an adult. In paediatric cases, fractures in the upper limb are more common than fractures in the lower limb (Saw, Fadzilah, Nawar, & Chua, 2011). Study carried out by (Saw, Fadzilah, Nawar, & Chua, 2011) concluded and found 69.8% of the most common bones treated for fracture were from the upper limb.

Out of all injury cases in children, skeletal trauma accounts for 15%. (Staheli L. T., 2008). It is vital to assess skeletal trauma, since it might be able to provide insight in in signalling a non-intentional injury or occurrences of unusual restoration (Ogden, 2000), which will eventually leads to further discovery, for example the child might have a medical disorder that alters the amount of time for a bone fracture to cure. For normal adults' bone restoration has been widely studied, however, the knowledge of bone fracture healing rates for paediatric cases is still remain sparse. Much to we know that the bone fracture healing rate among pediatric is faster as in comparison to adult as study suggested that might due to the child bone structure and also their youth (Ogden, 2000).

Our research used supervised and unsupervised artificial neural network to classify the healing rate of fractures in children. The lower limb algorithm to predict fracture healing time which was published will be utilised in this study (Malek S. , et al., 2018). We also developed an expert system based on rules (a knowledge rule-based expert system) to classify the type of fracture based on AO trauma guidelines (AO, 2017).

There are three sections in the lower limb long bones. Femur is the first part and also the body's largest bone starting from the hip joint to the tibia, where its major task is to carry out our regular physical activities. Tibia is the second part where it broadens at the proximal and distal boundaries and it is considered as the second largest bone, coherent at both the ankle and knee joints. Lastly, the third bone is fibula where it is joined together with tibia. Tibia and Fibula both forms the bones of the lower limb.

Same goes for upper limb long bones where it is also comprises of three parts; the humerus, radius and ulna. Firstly, the humerus is the single bone that runs from the shoulder to the elbow and the bone is located at the upper part of the arm. Then, the the scapula is attached to the humerus together with radius and ulna, the other the two bones of the lower arm. The radius and ulna are the long bones at the lower part of the arm. Both of them extended from the elbow to the wrist and parallel to each other. While the radius connects to the thumb side of the wrist, the ulna connects to the smallest finger.

When viewed from an anatomical position, on the medial side is where the ulna located while the radius is on the lateral side. Between the two bones, the ulna is longer and larger. Identifying the long bone in our human body is vital, where bone's shaft is oftenly determine by the direction of the line's fracture.

Research and studies regarding determine the paediatric fracture healing time is very much limited. Studies from (Zhao, et al., 2016) uses radiographic and x-ray fracture images combining with statistical approach to determine the recovery time of fracture (Tseng, 2013) suggested that the events leading to the injury are correlated to the fracture healing time that may able to give some perception whether it represent to another non-accidental injury or the laceration might have different healing rates. Thus, our studies will be focusing on predicting healing time among paediatric fracture as it considered beneficial and medical personnel including general practitioners and medical officers, they are able to use this system in the treatment process and follow-up period. Meanwhile in determining the type of fracture conventional method used is using AO trauma guideline (AO, 2017). The AO trauma guidelines system requires the user to identify the type of fracture where orthopaedic knowledge is essential in identifying the right type of fracture.

In the context of globalization, big quantity of data is produced and machine learning techniques have been oftenly applied in medical settings to help in classifying them, such as predicting various diseases and the information are then processed into a valuable format. Besides, with the constant improvement of the technology, machine learning methods have proof that it shows a higher accuracy for diagnosis as compared to the traditional statistical methods. In (Malek S. , et al., 2016) research, they have applied machine learning methods in the orthopaedic field using the Artificial Neural Network (ANN) and Random Forest (RF) methods in predicting fracture healing time in paediatric patients. In (Zhao, et al., 2016) study, they performed various machine learning methods including Support Vector Machine (SVM), Logistic Regression (LR), RF, and ANN in the study of osteoporosis in postmenopausal women for the measurement of bone mineral density. Besides, the results of the conventional clinical decision tool with the osteoporosis self-assessment tool (OST) is using screening screening femoral neck in postmenopausal women (Zhao, et al., 2016). As (Burges, 1998); (Cristianini & Shawe-Taylor, 2000) conducted studies focused on SVM for fracture risk prediction.

Supervised and unsupervised ANN are used to evaluate and predict paediatric fracture healing time and has been reported in some of the previous work. Firstly, (Malek S. , et al., 2016) used back-propagation on Multilayer perceptron (MLP) for supervised ANN. Unsupervised machine learning method used in (Malek S. , et al., 2016) is the Kohonen self-organizing feature map (SOM). The usage of SOM has been stated in (Collins & Evans, 1997) study, focusing on the investigation of the osteoporosis dataset, by applying the unsupervised learning method in classifying the dataset solving the problem of classifying osteoporosis whether the individual are having high chances of getting osteoporosis. The reason SOM been adapted in this study is mainly due to its visualization element, where SOM is capable to display a high dimensional of data (Kohonen, 1988). Besides, data with a high level of complexity, SOM able to cluster and plot the data with high similarities by then decreases the dimensions of data (Hollmen, 1996).

The well developed ML algorithm with the best performance, needs to be converted into a web-based application system for continuous assessment by the medical practitioners. Therefore, an online expert system with the function that is able to identify and predict the healing time of bone fracture for paediatric is essential. Potential users such as doctors, orthopaedic specialist and medical consultant should be consulted and interviewed for their suggestions, views and the requirements must be analysed to obtain a basic idea or requirement to be included in the system. Furthermore, more research, documentation and literature review should be conducted to obtain relevant information. This paediatric orthopaedic fracture prediction system aims to provide more insights for medical practitioners in handling bone fracture among children.

In developing the expert system, R and RStudio are used for the ML model development and web programming is used to developed rule-based fracture identification. Meanwhile, R is also used for integrating the ML model into the web-based expert system. The performance of the model is analysed, such as the ROC curve generated for the predicted healing time and also for statistical analysis using SPSS software. Microsoft SQL Management Studio is used to manage and develop the components of the module. Google Chrome is used to view and test the developed system.

1.3 Research Questions

- Which variables have the highest correlation with the time it takes for peadiatric bone healing fracture?
- Which artificial intelligence method is more suitable for predicting fracture healing rates in paediatric?
- How to apply and develop a expert system for identification of fracture types and predicting fracture healing time?

1.4 Objectives

- To developed an algorithm to predict fracture healing time using machine learning methods focusing on paediatric orthopaedic of the upper limb.

- To identify significant features that are associated with fracture healing time using RF and SVM feature importance method of the upper limb.
- To visualise significant factors associated with the fracture healing time of the paediatric upper limb using SOM method.
- To develop a rule-based expert system for determining the type of fracture and provide aftercare instructions for both the lower and upper limbs among paediatric.
- To construct an expert system that able to predict the healing rate of upper and lower limb fractures in children using machine learning approaches.

1.5 Problem Statement

Machine learning techniques have been widely explored and applied in the health industry, particularly in the treatment of hip fractures. However, there was no reference of machine learning in the field of paediatric orthopaedics. This study aims to assist medical practitioners that are not expert in handling paediatric orthopaedics in the task of identifying fracture type, aftercare guide and estimating the amount of time needed for the yooungsters required to recuperate. To overcome the knowledge gap between machine learning and paediatric orthopaedics, a systematic research strategy is required. As a result, this research thoroughly covers the application of machine learning in the field of medicine.

1.6 Scope of the Study

The project subjects to develop a an expert system that is targeted to identify the type of fracture and predict the bone fracture healing time for children at the ages 0 to 13 years. The model uses radiographs of lower limb of children of the year 2009, 2010, 2011 and 2014, as for the upper limb radiographs are obtained from the year 2010, 2014, 2015 and 2017, from the paediatric orthopaedic unit University Malaya Medical Centre (UMMC), as the ages from the date and time of initial injury was determined.

The type of fracture is identified and the full recovery time for paediatric bone fracture is estimated in this study. The lower limb algorithm for fracture healing time from (Malek S. , et al., 2018) will be embedded into the system with upper limb prediction model. It aims to determine the healing time of paediatric injuries in both the upper and lower limbs using machine learning methods. With the machine learning model for predicting the healing rates of bone fracture, this study also aims to include an expert system component that will determine the type of the fracture and provide patient aftercare guidance.

SVR and RF are the two supervised machine learning algorithms and were adapted in the development of the prediction models. Meanwhile, unsupervised method used in this study is SOM where it was applied in the analysis of the association between fracture healing time and fracture parameters. The backward elimination method is one of the feature selection was used to determine significant variables. It works on eliminating redundancy and irrelevant features to identify the most significant predictors in each model. Machine learning with the optimum performance is chosen to incorporate into the proposed system. The prediction outcome will guide them to provide the most suitable treatment and medical care for a particular patient. The users are allowed to predict the healing rates based on the patient condition which allow medical practitioners to analyze and discuss the predicted outcome. The records will be saved to future view, update or even delete certain data. A rule-based expert system is developed in this study, where the knowledge is represented in the set of rules. Each rule specifies a relation or recommendation and has the IF (condition) and THEN (action) structure. The reason is reducing the amount of risk in terms of system accuracy, especially in making decision-related to human health. The system gives a steady response where it is dependent on the rules, and the output is not vague.

1.7 Project Overview

The organization of the thesis as follow:

Chapter One – Introduction

An overview of the project as well as an introduction to it is included in this chapter. The research aims, problem statements, and scope of this study are described in this chapter.

Chapter Two – Literature Review

Chapter 2 is the literature review for the research. It covers the basic understanding of limb fractures especially on an immature skeleton, machine learning methods and analysis, and model validation. It reviews past studies and researches done for the machine learning model development for paediatric orthopaedic studies and also the available online system related to paediatric orthopaedics. This chapeter also discussed about the Decision Support System and Expert System. Overall, this chapter contains information from general view to a specific idea about the study field in this research.

Chapter Three – Materials and Methodologies

This chapter discusses the methodologies and steps in model development such as machine learning methods feature selection that has been applied in predicting the healing rates of upper and lower limb fracture among children. The chapter also discusses the decision-support part of the system. The requirements of the system such as fact-finding, hardware and software requirement, Workflow Diagram, Data Flow Diagram (DFD)and Entity Relation (ER) Diagram is included in this chapter as well.

Chapter Four – Results and Discussions

This chapter presents the results from the machine learning model, which includes variable importance, RMSE error, the discrepancy between the expected healing time and the actual time needed to recover from a fracture. It also presents and discusses the decision support and user interface of the developed system. The chapter also includes system evaluation metrics.

Chapter Five – Conclusion

This chapter discusses the results obtained in chapter four, using the machine learning method to determine the variable importance, machine learning algorithms in the paediatric fracture healing time and usage of SOM application to analyze the outcome. We also discussed the limitation of the system and what can be done to enhance the system in the future and the conclusion of the study.

CHAPTER 2 - LITERATURE REVIEW

2.1 Orthopaedics

According to Davis from Medical News Today, Orthopaedics is a branch of medicine that focuses on the diagnosis and treatment of musculoskeletal diseases. Muscles and bones, as well as joints, ligaments, and tendons, make up this system. Some of these issues are present from birth, while others may emerge as a result of an accident or normal ageing. An orthopedist is a person who specializes in orthopaedics. It treats a range of musculoskeletal injuries and diseases, including musculoskeletal trauma, spine diseases, sports injuries, degenerative diseases, infections, tumours, and congenital problems, using both surgical and non-surgical methods (Davis, 2020).

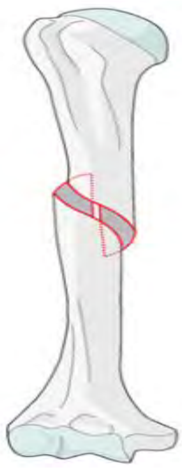
2.2 Paediatric Orthopaedics

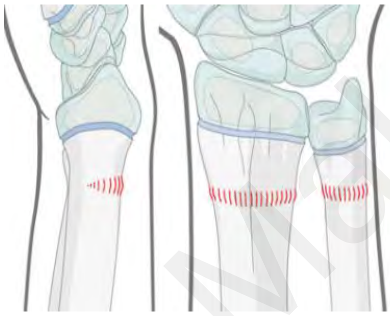
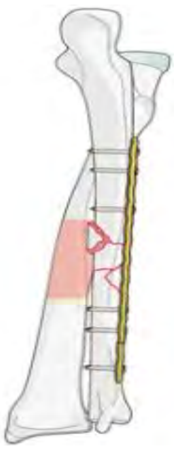
Pediatric orthopaedics is a medical discipline that focuses on the prevention and treatment of musculoskeletal problems in children. According to Md, there is a large proportion of orthopaedic problem originates during the early period of growth. It is vital to understand the normal and abnormal growth and development of the musculoskeletal in paediatric and to improve our understanding of the cause of disease and better in managing the carried orthopaedic problems that occur in childhood (Md, 2015, pp. 1–3). Children's fractures (ages 0–12 years) differ significantly from adult fractures in terms of appearance. Injuries to the skeleton account for 15% of all injuries in children. (Budd, 2012).

2.3 Bone Fractures

A medical situation where the continuity of the bone is broken is usually referred as a bone fracture, usually involving cortex of the bone. High force impact or stress causes a substantial percentage of bone fractures (Nordqvist, Petersson, & Redlund-Johnell, 1998). Children's fracture has different features compared to adults' bone fractures as it can arise in both partial and complete fracture of the bone (Staheli L. T., 2008). The anatomy and biomechanics of paediatric bones are different from adult bones which leads to different paediatric fracture patterns, healing mechanisms and management. Fractures can be caused by a direct hit from a heavy item, a twisting injury, or an angulating injury. (Budd, 2012). Table 2.1 below shows the common type of bone fractures.

Table 2.1: Common Types of Bone Fractures

Types of Fracture	Images	Descriptions
Transverse fracture		High-energy trauma frequently results in transverse fractures. They have good axial stability and don't tend to shorten when loaded.
Spiral fracture		Simple diaphyseal fractures with a spiral fracture line that can occur at any level of the diaphysis. Trauma with a rotating force frequently results in simple spiral fractures. They have axial instability.
Oblique fracture		The inclination of an oblique fracture line with regard to the

		perpendicular to the axis of the bone is equal to or greater than 30º. Simple oblique fractures are a result of trauma with a rotational force. They are axially unstable.
Torus(buckle) fracture		A buckle/torus fracture typically occurs in very young children. Always consider deliberate injury in non-ambulant children with a femoral fracture. The fracture is intrinsically stable and heals rapidly. If seen in older children, it is often an indication of underlying bone disease.
Comminuted fracture		High-energy trauma, such as car accidents, is the main reason of commimuted fracture. They are axially unstable.

2.4 Fracture Anatomy

As illustrated in figure 2.1, the area of a long bone are divided into three different zones: epiphysis, metaphysis, and diaphysis. The epiphysis and metaphysis are separated during development by a fourth zone called the epiphyseal plate, or physis. This cartilaginous section of the bone is the origin of the bone's longitudinal growth. All epiphyseal plates have closed by maturity, leaving just a bony scar as a reminder of this crucial structure. Long bones including femur, tibia, fibula which located at the lower limb, as the humerus, radius, ulna are located on the upper limb.

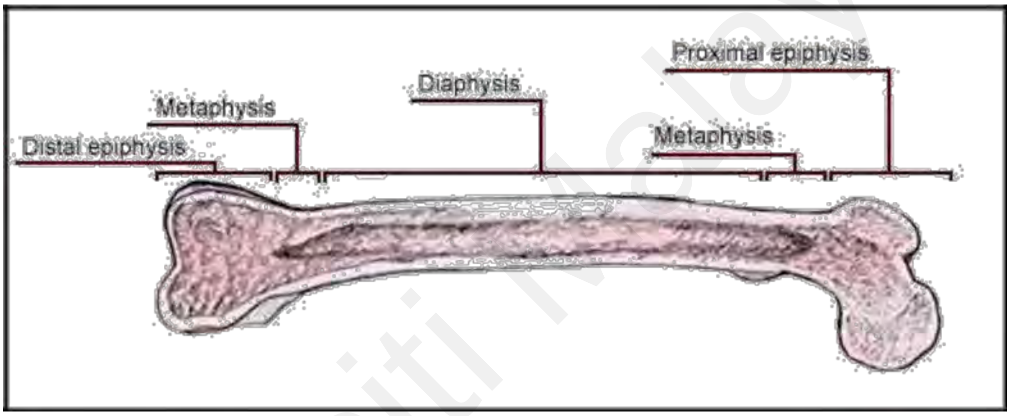


Figure 2.1: Region of a Long Bone (Khetrapal, 2018)

According to (Arora, Fichadia, Hartwig, & Kannikeswaran, 2014), the most common fractured bone in the upper limb is the distal part of the radius. Together with the metacarpals (hand proper) fractures and the phalanges fractures, it adds up to 50% of all fractures. In paediatric cases, one of the most frequently fractured bones is the clavicle which is responsible for 10 to 15% of the total fractures. Less than 0.45% of paediatric fractures are proximal humeral fractures which are comparatively rare.

Other uncommon paediatric fractures that account for 2 to 5.4% are humeral shaft fractures. The most frequent paediatric elbow fracture is the supracondylar humeral fractures which account for 3% of all paediatric cases. The next common paediatric fracture in the elbow is the lateral condyle fractures that are responsible for

12 to 20% of all distal humeral fractures. According to (Arora, Fichadia, Hartwig, & Kannikeswaran, 2014), the most common paediatric fractures are the distal radius and ulna fractures which account for more than 75% of all forearm fractures.

Torus or buckle fractures happen when there is a compression on the bony cortex causing it to bulge, without extending the fracture further into the cortex (Figure 1). Statistically, about 1 in 25 children experiences buckle fracture. This fracture type accounts for 50% of all wrist paediatric fractures (Ben-Yakov & Boutis, 2016).

The direction of the fracture line to the shaft of the bone is used to characterise long bone fractures. Several forms of fractures from radio-graph samples are discussed in Table 2.2.

Table 2.2: Radiographs of Common Fractures

Types of Fracture	**Descriptions**	**Images**
Transverse Fracture	The transverse fracture of the tibia occurs when the long bone's shaft is at right angles to the fracture.	
Spiral Fracture	The fracture line spirals around the shaft of the long bone as a consequence of the twisting injury.	
Buckle/Torus Fracture	An example of an oblique	

	kind of fracture occurs in the metatarsal area, most probably the fracture travels at an angle oblique to the shaft of the long bone.	

Fracture remodelling is the process that happens throughout time as the bone reshapes itself to an anatomic position that is also referred to as the healing time of the fracture. Younger children have greater potential in remodelling the fractures (Budd, 2012). Paediatric bones have a greater capability for healing and remodelling than adult bones. The lower elasticity modulus of paediatric bone in comparison to the adult bone causes higher absorption of energy before failure. Increased porosity of the bone inhibits fracture propagation, resulting in a decrease in the frequency of comminuted paediatric fractures (Budd, 2012). Thus, The time it takes for a child's bone to fully recover is most likely half that of an adult's corresponding fracture (Ogden, 2000).

It's critical to discover out whether the skeletal trauma was caused by a non-accidental occurrence or whether the healing was abnormal, because the latter might indicate an underlying medical issue that impairs bone regeneration. While healing rates for a normal fracture procedure have been documented in adults, nothing is known about healing rates in children. In comparison to adults, paediatric bone physiology shows that younger people recover faster (Ogden, 2000).

In paediatric cases, fractures in the upper limb are more common than fractures in the lower limb (Saw, Fadzilah, Nawar, & Chua, 2011). Results from (Saw, Fadzilah, Nawar, & Chua, 2011) study, found that 69.8% of the most common bones treated for fracture were from the radius and/or ulnar and humerus. It is exceptionally important in assessing the fracture patterns, especially in paediatric cases as it may signal a potential non-accidental injury or abnormal healing. Fracture pattern analysis is also important in helping cases of accident reconstruction (Cohen, et al., 2016).

The upper limb's long bones are divided into three groups.:

- Humerus: long bone of the upper limb, which extends from the shoulder to the elbow.
- Ulna: a long bone in the forearm, which lies medially and parallel to the radius, the second of the forearm bones.
- Radius: Together with the ulna, the radius is a long bone in the forearm. It lies laterally and parallels to the ulna, the second of the forearm bones.

The long bones of the lower limb are classified into three parts:

- Femur: the longest bone in the human body, so it can transmit forces from the hip to the tibia.
- Tibia: second largest bone, expand at the proximal and distal ends.
- Fibula: together with the tibia it forms the leg of the long bones.

2.5 Upper Limb Anatomy

The region that is from the deltoid and going up and including the hand, the arm, axilla and the shoulder is identified as the upper limb (Malone, Sauer, & Fenton, 2011). The upper limb as illustrated in figure 2.2 can be distinguished into the following regions; shoulder, arm, forearm and hand. The first region which is the shoulder comprises the pectoral (breast region), the axilla (armpit), and the scapula. Next, the second region is the arm that is also known as the upper arm is located in between the shoulder and the joints of the cubitus (elbow). The third region is the forearm or antebrachium which runs from the elbow to the joints of the wrist. The fourth region is the hand or manus, which is placed distal to the wrist. The hand includes the carpus (wrist) and metacarpus (hand proper).

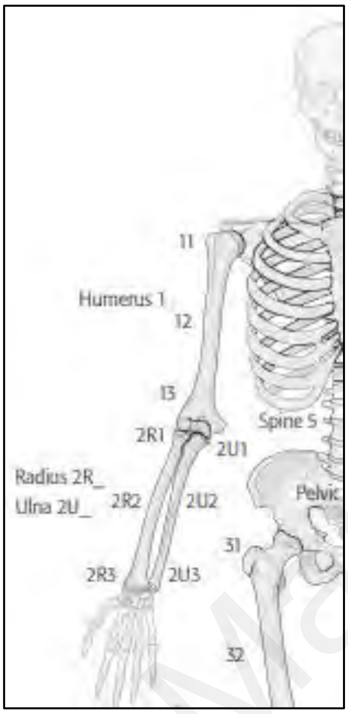


Figure 2.2: Region in Upper Limb (AO, 2017)

In the region of the upper limb, there are three types of long bones. The humerus is located in the upper arm region. At the proximal end is a single bone and the smooth and round region which is located at the humerus head. The other parts which are at the distal end of the humerus contain the articulation areas which join the remaining long bones; radius and ulna, forming the elbow joint. The medial bone located in the forearm region is the ulna. Ulna's proximal end appends to the humerus's distal end forming the elbow. The head of the ulna is the small, rounded area found at the ulna's distal end. Ulna runs in parallel with the radius, the lateral bone in the forearm region. Contradicting to the ulna, the disc-shaped radius head is located at its proximal end while at its distal end, the radius has articulating areas to form joints for the wrist. (OpenStax, 2016).

Upper limb fractures frequently happened in children and are responsible for nearly 75% of all paediatric fractures. The rate of fracture remodelling depends on the following factors; the closeness of the fracture to the physis, the distortion plane, the children’s age, and the presence of hidden bone disease.

2.6 Lower Limb Anatomy

The lower limb bones are divided into four sections as illustrated in figure 2.3 which are femur, tibia, fibula and foot. The only bone in the thigh is called femur. It is classed as a long bone and is the longest bone in the human body, where it is responsible for transmitting forces from the tibia to the hip joint. Many muscles and ligaments have their origins and attachments here. The tibia, often known as the shin, is the major bone of the leg. It articulates at the knee and ankle joints, extends at the proximal and distal ends. It is the body's second-largest bone.

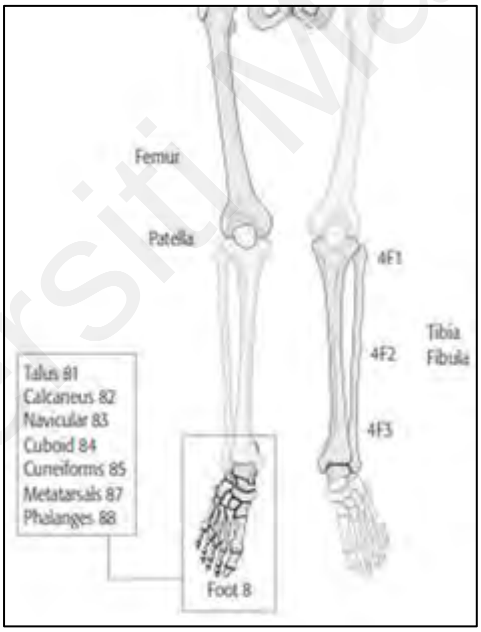


Figure 2.3: Lower Limb Region (AO, 2017)

The fibula is much thinner when compare ro tibia, it is located laterally to tibia. The main function of the fibula is to act as an attachment for muscles. The fibular shaft has three surfaces; anterior, lateral and posterior. Distally, the lateral surface continues inferiorly and is called the lateral malleolus. The lateral malleolus is more prominent than the medial malleolus and can be palpated at the ankle on the lateral side of the leg.

The epiphysis of the distal femur is present at birth among paediatrics. The physis at this location is responsible for 70% of the growth of the femur with almost 1 cm longitudinal growth per year. It closes between 14 and 17 in females and between 15 and 19 in males with wide variability in age.

2.7 Importance of Child's Skeleton Care

From the perspective of skeletal injury, a child is any young person who has not yet reached skeletal maturity. Legal definitions often include all persons under the age of 18 years, irrespective of skeletal maturity, however, it varies from different countries. Injured children differ from injured adults in several respects, thus post-traumatic care for adult and child patient also different as well.

Every child has the right to the best possible health. The special needs of injured children are best met in a dedicated paediatric trauma unit. For serious injuries, prompt transfer to a specialist unit, whenever possible, is advisable. Even for minor injuries, specialist follow-up care is desirable.

Children's fractures can often be managed nonoperatively as best by paediatric orthopaedic expert. Since, they do not like being confined to bed, to have their arm or leg in a cumbersome plaster cast, or to be restricted in their play or ability to move around. There is a dedicated commentary principle on the nonoperative treatment of children's fractures as well.

Injuries can often have an impact on future skeletal growth. Additionally, growth can result in satisfactory modelling of malunion. Any child with an unexplained, or insufficiently explained, injury, especially fractures at multiple sites, or of an unusual pattern, must be investigated as a possible victim of nonaccidental injury. Possibly lead to post-traumatic growth disturbance.

2.8 Healing Rates

Fracture healing is a sequence of processes that restores the damaged bone to its pre-fracture condition (Aiyer, 2018). It involves a complex interrelation between biomechanical, anatomical, and biochemical processes (Buza & Einhorn, 2016). If the mechanism of the healing process fails to restore the fractured bone in a specific period, it may result in delayed healing, For determining bone fractures, there are a few different forms of unity. As we may see fractures that do not heal as expected such as delayed union, non-union, or malunion.

A normal union is considered when the fractured bone unites within a normal period. (Buza & Einhorn, 2016) stated that no standard guideline exists in diagnosing a fracture as non-union. A non-union fracture is defined as incomplete fracture healing within a period of 9 months after the fracture occurs by the FDA (Food and Drug Administration), in addition to no healing improvement on serial radiographs for three months in a row (Panteli, Pountos, Jones, & Giannoudis, 2015). According to (Buza & Einhorn, 2016), 5 to 10% of all fracture cases in the United States accounts for delayed union fractures. Out of the delayed union fracture cases, nearly 16% progresses to non-union cases. Perkin's timetable shows the guideline in explaining the time taken for a new fracture to recover. An united fractured in deformed structure due to tilted, twisted or shortened is defined as malunion. Osteoarthritis of the knee or ankle often leads to various deformity in the leg (Simonis, Parnell, Ray, & Peacock, 2003). It takes a long time for a delayed union to heal. Table 3 discussed a few types of bone healing.

The bone structure of a kid differs from that of an adult. These distinctions are critical for the proper diagnosis and management of fractures. (Staheli & Lynn, 2003). The rate of bone healing in adults are similar to paediatric bone healing as the fracture and bones are similar to one another. They both go through the three same phases of inflammation, reparation, and remodelling. However, there are still differences in the healing of paediatric bone, where is mostly due to those differences between paediatric and adult bone (Lindaman, 2001).

Furthermore, bone angulation is consider as one of the factors affect the time of healing for a fracture. In (Noonan & Price, 1998) studies stated that fracture is a result of deformities comprises of indirect trauma combined with rotational displacement, and bone angulation is one of the factors in detemining the fracture treatment and the healing time.

Due to a larger, stronger, and more active dense fibrous membrane (periosteum) covers the surface of a child's bone, the fracture heals faster than an adult's. (Staheli & Lynn, 2003). Blood veins in the periosteum deliver oxygen and nutrients to the bone cells, where this greatly help in the fractured bones remodelling by supplying enough nutrients to the injured section (Calmar & Vinci, 2002). The periosteum in children causes a more rapid union of fractured bones and an increased potential for remodelling (Staheli & Lynn, 2003). Table 2.3 as shown below summarized the types of bone healing.

Table 2.3: Types of Bone Healing

Types of Bone Healing	Normal Union	Delayed Union	Malunion	Non-Union (pseudoarthrosis)
Types	Normal Healing	Disturbed Healing	Disturbed Healing	Disturbed Healing
Descriptions	Occurs naturally after the traumatic bony disruption.	Fracture healing takes about twice as long as expected for a specific location.	Healing in a non-anatomical position. Can be partially compensated for by remodelling of the bone.	No visible progressive signs of healing for 3 months
Average Time to Heal	3 -12 weeks	3 – 6 months	Treatment needed to be given to correct the alignment of the bone.	Healing has stopped.

For the same fracture in teens, a child may take half of the time for the fracture to heal (Gupta, Alderliesten, & Benedictus, 2015). Moreover, upper limb fractures heal faster compared to lower limb fractures in adult cases. The same rate can be assumed for paediatric fracture cases (Malone, Sauer, & Fenton, 2011). The radiological assessment shows the forearm fracture in adult cases may indicate union in 8 weeks, while in paediatric cases, the same fracture heals faster (Baitner, et al., 2007). Perkin's timeline is a useful tool for determining the duration it takes for a new fracture to heal. It is shown below in Table 2.4.

Table 2.4: Perkins classification of fracture healing time (in weeks)

PERKIN'S CLASSIFICATION	Spiral		Transverse	
	Union	Consolidation	Union	Consolidation
Upper Limb	3	6	6	12
Lower Limb	6	12	12	24

Children's lower limb fractures generally occur in half the period shown in figure 2.3, i.e. 3 to 6 weeks for spiral fractures and 6 to 12 weeks for transverse fractures. Non-union took place at least nine months after the tragedy. Over the previous three months, there has been no indication of X-ray alterations in the union. Fresh fractures might take up to 18 months to heal in rare circumstances. (Simonis, Parnell, Ray, & Peacock, 2003).

Few studies (Morshed, Corrales, Genant, & Miclau III, 2008) (Rozental, Vazquez, Chacko, Ayogu, & Bouxsein, 2009) have looked at how to classify paediatric fracture healing based on radiographic fractures and how to calculate healing rates using a statistical method. Injuries that heal irregularly or suggest a non-accidental injury may benefit from correlating healing time with the chronology history of the injury. The system for predicting the healing time required should serve as a tool in the process of treatment for general practitioners and medical officers and the follow-up period.

(Malek S. , et al., 2018) published paper using machine learning algorithm for lower limb fracture will be applied in this study. Random forest (RF) and Self Organizing feature Maps (SOM) methods was used in Malek, S. et al. (2018) study focus on examined the children lower limb fracture healing rate. The study sample was obtained from the pediatric orthopedic unit in University Malaya Medical Centre.

Radiographs of long bones from children aged 0–12 years with lower limb fractures including the femur, tibia, and fibula. The following characteristics were retrieved from radiographic images: type of fracture, angulation of the fracture, percentage of contact area of the fracture, age, gender, bone type, type of fracture, and number of bones involved. The RF method is first used to prioritise the most significant factors that influence bone healing time.

Then, using SOM, the connection between the chosen factors and fracture healing time was investigated. This study examined fractures in children cases with the age range from 0 to 12 years old, especially upper limb fractures. Children's bone fractures contain different morphology and characteristics compared to adult fractures. Limited articles are available in assessing the classification system of paediatric fracture healing with statistical approaches in predicting rates of healing. By predicting the healing time and correlates it with the fractured history, it may help in signalling a non-unintentional injury or abnormal restoration cases. Prediction of the fracture healing time is a system that is useful for the treatment process, especially for physicians and orthopaedics and in the follow-up period.

2.9 Differences between General Orthopaedic and Paediatric Orthopaedic

Similar injuries occur in adult and a child's body often has different responses. Therefore, paediatric orthopaedic surgeons are a person who is specific training to evaluate and treat children. The main differences including the bone anatomy, the presence of growth plates in a child's bone, injuries, syndromes, deformities and gait abnormalities (OrthoStreams, 2020). Besides, paediatric orthopaedic specialists have a better understanding in examine and treat children in terms of communicating with them and dealing with child musculoskeletal problem (Davis, 2020).

According to (Hennig, Staats, & Rosenbaum, 1994), a child's bones are very different from those of an adult. As a child's bone is softer in structure when compare with adults, sooner or later, the bones will gradually develop into calcified bones when the child getting older. Besides, paediatric orthopaedic specialist deals more with a child growth plate, since fracture can occur within or near the growth plates, that requires different treatment compared to fractures in adults. Next, the healing rate of a child's bones is faster than adult bones, thus to ensure the child's bones heal correctly, different surgical techniques needed to be applied.

In (Zargarbashi, et al., 2017) research, They compared the treatment of developmental dysplasia of the hip and flexible flatfoot by paediatric and general orthopaedic surgeons. According to the findings, there is a lack of consensus on therapeutic techniques for frequent paediatric orthopaedic cases, necessitating a more thorough examination. In contrast, In the treatment of developmental dysplasia of the hip and flexible flatfoot, general orthopaedic surgeons have reached an agreement. According to the findings, existing certified criteria were critical in achieving consistency, maximising diagnostic and therapeutic output, and reducing needless work-up.

2.10 Machine Learning

According to (Alpaydin & Ethem, 2020), machine learning (ML) is computer programming that was used to optimize computer performance by using sample data. It built mathematical models based on the theory of statistics. It functioned by recognizing a certain pattern from train data to construct good and accurate assumption and prediction. It can be considered as part of artificial intelligence because it can learn and adapt to the changing environment, providing solutions for all possible situations.

Therefore, it was common for solving complicated problems, especially in the science field.

A study carried out by (Paluszek & Thomas, 2016), stated that ML allows computers to decide to base on experiences, reaction and actions. ML has been successfully used in many fields of medicine, bioinformatics, biology, business and many others. Machine learning has advantages over statistical approaches for prediction, such as simplifying the process of acquiring knowledge from a system or lowering time consumption (Kesavaraj & Sukumaran, 2013).

(Kononenko & Kukar, 2007) states that The quality of machine learning classification algorithms is determined by the classifier chosen, and it was determined that combinations of classifiers are more trustworthy in a diagnostic system problem than a single classifier. Besides, data pre-processing and tuning of algorithms classification highly impacting the machine learning performance (Kesavaraj & Sukumaran, 2013). Having proper data for ML algorithms is very important for training and testing ML algorithms.

Several ML techniques have been deployed in developing and validating prediction models (Mansoor, Elgendy, Segal, Bavry, & Bian, 2017). The subsections as follow provide an overview of the classifiers consistent with the research which include supervised learning - Support Vector Machine (SVM), and Random Forest (RF) and unsupervised learning - Self-Organizing Map (SOM).

In this study, Both supervised and unsupervised ANN is adopted for the upper limb fracture healing time. In supervised learning, an error between the layer's answer and the actual data is minimised at each network layer. The network's actual output is compared to the predicted output for that particular input. As a result, an error value is generated. The network's link weights are gradually changed until the right output is generated.

For unsupervised learning Kohonen self-organizing feature map (SOM) is used in this study. SOM is applied in the upper limb fracture data because it able to discover several important properties which may be utilised in the process of knowledge discovery and exploratory data analysis. Specific architecture like the Hopefield network or Kohonen network is implemented by connecting the neurons in which they learn through the process of self-organization (Navarro & Bennun, 2014).

Machine learning algorithm can be classify as supervised and unsupervised learning. In this research, both types of ML algorithms were used.

2.10.1 Supervised Learning

Supervised learning is defined as when data with corresponding correct outputs is provided during training for predicting the future unknown outputs of a given instance. The common algorithms are; Random Forrest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN) and Decision Tree (DT), (Chandralekha & Shenbagavadivu, 2018).

Supervised ML models have been used to build predictive models for medical diagnosis (Maroco, et al., 2011). Supervised learning was used to train the model based on the sample dataset by giving that targeted output provided. It was applied in classification and regression tasks. Normally, the sample dataset will be divided into a training dataset and testing dataset whereby the training dataset was annotated whereas the testing dataset was not annotated. Features and annotations in the training set are used to predict the outcome in the testing set in a model. However, the targeted output was provided to compare with the predicted output to increase the accuracy of prediction. If the result was not satisfied, the model is going to train again. (Fabris, De

Magalhães, & Freitas, 2017). Figure 2.4 illustrates ML supervised learning in graphical form.

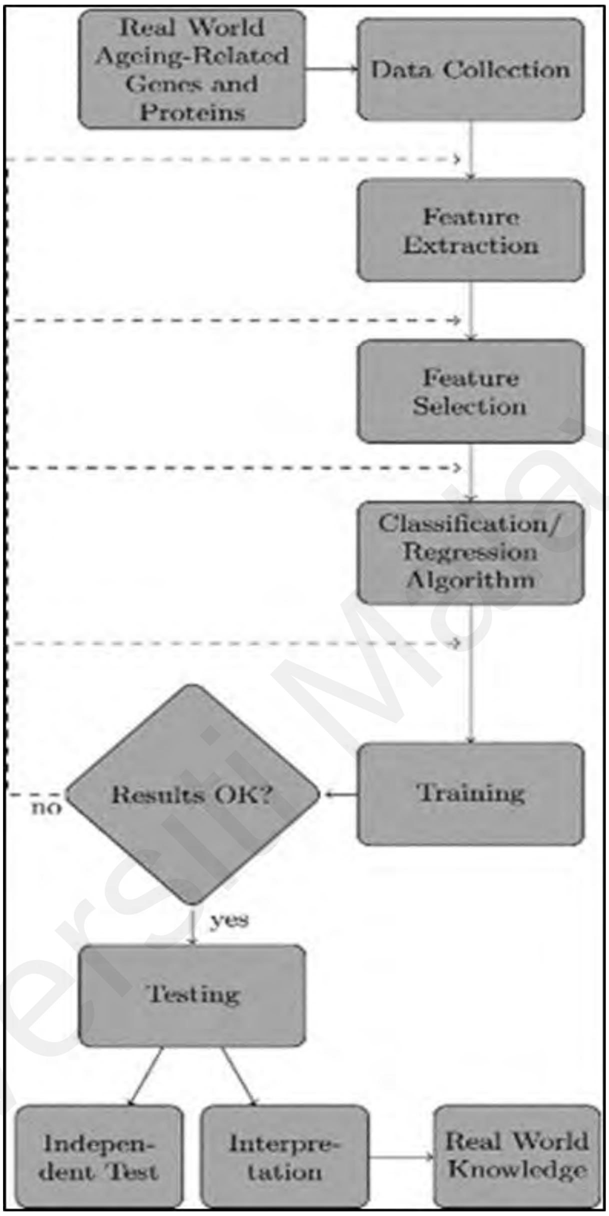


Figure 2.4: Supervised Learning Flowchart

Random Forest (RF)

According to (Ho, 1995), RF is a method that will generate multiple decision trees based on the training data given. It splits the data into smaller and smaller trees, resulting in multiple trees and generates significant predictors that will influence the outcome. Nowadays, RF is a common method because it worked well in avoiding overfitting and increasing the prediction accuracy.

RF is an ensemble method that building decisions trees and incorporates the important predictors and their interaction during the learning process. Hence, there showed a rise in RF application in computational biology because it was nonparametric, interpretable, efficiency and accuracy for many types of data. (Qi, 2012).

(Sammut & Webb, 2011) defined that RF is a hybrid of bagging algorithm and random subspace method. It used decision trees as the base classifier. Each tree is constructed from a bootstrap sample in the original dataset. RF method was unpruned, therefore it avoided overfitting. The random subset method was used to identify the feature and the subset size is split at each branch in the tree to obtain the diversity of the classifiers. Both methods yielded low bias and high variance but low correlation trees. Combining the trees to achieve low bias and low variance forest.

RF, as shown in figure 2.5, is an ensemble approach that constructs multiple decision trees from boostrapping samples, which are then grouped together using a classification or regression method with extra randomization (Breiman L. , 2001) (Liaw & Wiener, 2002). Only a subset of predictor is randomly chosen from the full set of predictors, *p*, at each node in RF (Genuer, Poggi, & Tuleau-Malot, 2010) which is denoted by *mtry* and the best split is done by Gini index node of impurity. Gini index of impurity is a measure of the class label conveyance at each node and is calculated only among the subset of predictors. The value of Gini impurity is 0 and 1 where 0 indicates when all the predictors at the node are of the same class (Khalilia, Chakraborty, & Popescu, 2011).

The decision on selecting the best split is based on the lowest Gini impurity value among the predictors to reduce the error rate, at each nodes of the tree. The default value of *mtry*=p1/2 is set for classification and *mtry*=p/3 for regression). Pruning is not required in RF therefore the trees generated are maximal, low-bias and low correlation among the trees (Díaz-Uriarte & De Andrés, 2006).

Bootstrap aggregation can be short-form as bagging. (Breiman L. , 1996) demonstrated that each tree was built based on random samples from the training set where replacement may occur, resulting in different trees. Hence, RF used bagging method to build large and not correlated trees and then average them. It draws a random subset of features for training the individual trees, resulting in better predictive performance. It is simpler to train and tune (Breiman L. , 2001).

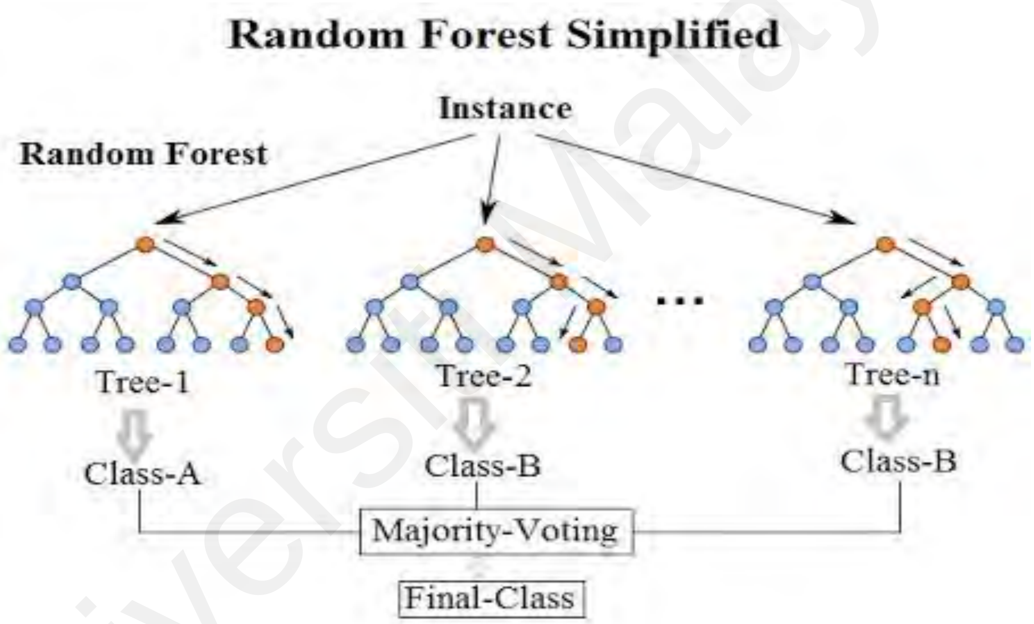


Figure 2.5: Random Forest Diagram (Koehrsen, 2020)

RF performance is superior compared to performance over single tree classifiers such as CART, and yield generalization error rates that compare acceptably to other statistical and machine learning methods (Biau, Devroye, & Lugosi, 2008). RF are noted to be the best general-purpose classifiers present (Breiman L. , 2001).

RF method gave a good performance and played an important role in the medical field (Masetic & Subasi, 2016). In this study, RF method have been used for fracture healing time and variable selection. RF is used not only for prediction, but also to assess variable selection and importance.

Support Vector Machine (SVM) and Support Vector Regression (SVR)

SVM is a supervised training algorithm that can be useful in the purpose of classification and regression (Vapnik, Golowich, & Smola, 1997). SVM had been widely applied in pattern recognition for data analysis and to test the performance of the provided dataset. SVM can be used to analyse data for classification and regression using algorithms and kernels in SVM (Cortes & Vapnik, 1995). SVM is a powerful tool in data mining, in which it works to discover patterns on a given dataset, which will help to enhance our understanding the analysed data and improve its prediction.

SVM can be used to model and predict responses in linear and non-linear data dealing with high-dimensional data such as gene expression (Schölkopf, Smola, & Bach, 2002) (Ben-Hur, Ong, Sonnenburg, Schölkopf, & Rätsch, 2008) (Karatzoglou, Meyer, & Hornik, 2006). SVM technique for classification goal is to use vector of explanatory variables to estimate the optimal decision boundary that best separates the class labels (Cortes & Vapnik, 1995) (Clarke, Fokou´e, & Zhang, 2009). SVM uses optimization parameters in case of grid search which is known as large margin classifier. In the simple binary cases, the two classes separate linearly and the boundary between the two classes is called the hyperplane. Kernelization of the SVM classifier enables the actual learning to take place in the feature space. The kernel function returns the inner product between the images of two data points in feature space (Karatzoglou, Meyer, & Hornik, 2006). This referred to in literature as the “kernel trick” (Schölkopf, Smola, & Bach, 2002).

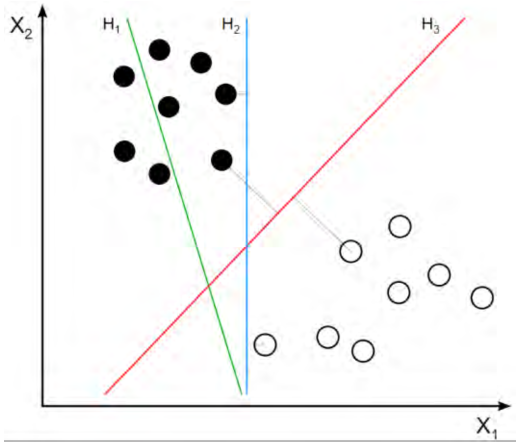


Figure 2.6: H3 separates the data points with the highest margin

Support vector classification (SVC) constructs a hyperplane that divides two classes equally. SVC is first created to address the linearly separable cases. Then, kernel tricks are used for non-linear cases. Hinge loss function is introduced for cases that are non-linearly separable.

$$\max\left(0,1 - y_i\left(\underset{w}{\rightarrow} \cdot \underset{x_i}{\rightarrow} - b\right)\right)$$

Where y_i is the ith target and $\left(\underset{w}{\rightarrow} \cdot \underset{x_i}{\rightarrow} - b\right)$ is the current output.

If x_i is one the right correct margin side, the hinge loss function will be 0. Otherwise, the function's value will be proportional to the distance from the margin (Rosasco, Vito, Caponnetto, Piana, & Verri, 2004).

SVR applied in this study has the same principle as SVM for classification cases. (Vapnik, Golowich, & Smola, 1997)proposed SVR where the response variable is numerical rather than categorical. The SVR output model does not rely on the dispensation of the hidden variables; dependent or independent. SVR is a non-parametric technique that depends on kernel functions and uses the principle of maximal margin as a convex optimization problem.

Support Vector Regression (SVR) algorithm tries to lower the error bound generalization to reach a performance generalization rather than lowering down the training error. Error bound generalization is a total of the training error and a regularization expression which manages the twist in space of the hypothesis (Basak, Pal, & Patranabis, 2007).

For SVR cases, a different loss function is used, the epsilon intensive loss function. The function neglects errors located within the true value certain distance. The loss function is used to ensure the optimization of trusted bound for generalization (Basak, Pal, & Patranabis, 2007).

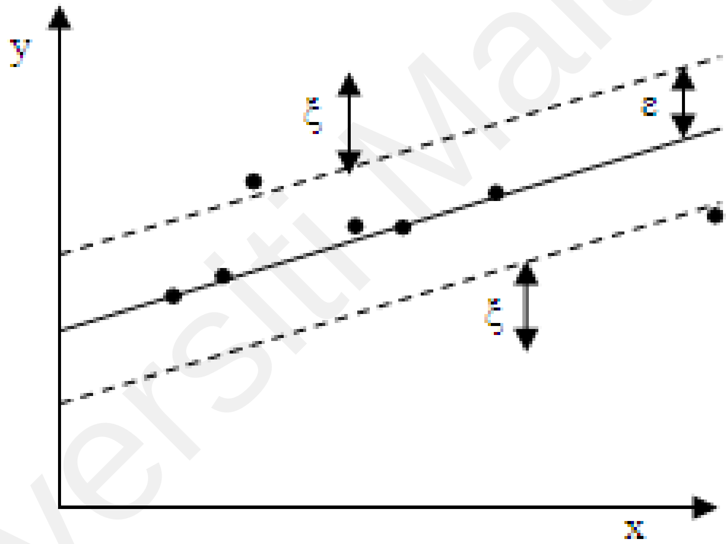


Figure 2.7: One-dimensional linear regression with epsilon intensive band.

In order to avoid over-fitting, cost parameter is implemented in SVR. Cost parameter is a measure of how many errors of misclassifications is allowed during training phase. SVR model used in this study is computed using ‘caret’ package. SVR technique uses kernel functions to construct the model.

Some popular kernels in SVM are:

1. Polynomial Kernel: $K(X, Y) = (x^T y + c)^d$, where x and y are input space vectors.

2. Fisher Kernel: $K(X_i, X_j) = U_{X_i}^T I^{-1} U_{Xj}$, where I represent Fisher matrix

3. Radial Basis Function (RBF) Kernel: $K(X, X') = \exp\left(-\frac{\left\|x - x'\right\|^2}{2\sigma^2}\right)$, where x and x' are feature input space vectors.

In this study, linear kernel is selected in to rank the variable importance. Radial basis function (RBF) kernel was used with backward elimination to develop the model. RBF kernel can reduce the computational complexity of the training procedure while giving good performance under general smoothness assumptions. Besides, in this study SVR performed a better result compared to Random Forest algorithm for the upper limb dataset, the result will be discussed in the next few chapters.

2.10.2 Unsupervised Learning

In the family of ML algorithms, unsupervised learning is considered as one of them and mostly is applied in pattern recognition and descriptive modelling. The main contrast with supervised learning is there are no output categories or labels based on which the algorithm can try to model relationships (Honkela, Pulkki, & Kohonen, 1995).

Unsupervised learning methods utilised the input information and processes as a set of rules, pattern detection and grouping and summarized the input data points, which is useful in extracting meaningful insights and visualize and describe the data better, since the input data is unlabelled. One of the most common unsupervised learning algorithm is SOM which had applied in the study of upper limb fracture data.

Self-Organizing Map (SOM)

Self-Organizing Map is also known as SOM or Kohonen's SOM; it is an topological mapping unsupervised mathematical model. Unsupervised competitive learning allows SOMs to learn on their own, where it attempts and maps the weight to fit in the dataset. The topology relationship among inputs is conserved once plotted to SOM that is suitable for representing complex data. SOMs enable users to describe multidimensional data in one or two dimensions in a considerably lower-dimensional domain (Kohonen, 1988).

SOM consists of two main Kohonen layers. The input layer of neurons in SOM are connected to the Kohonen layer. The input layer is presented and linked to all neurons which their connection is established in weight which vary for every iteration adaptively. A small value of weights is designated randomly to the input vector which later the space among the input and the summed weights are calculated in each of the neurons (Chaudhary, Bhatia, & Ahlawat, 2014).

This technique also retains the topological mapping from input space to output space, making it an excellent tool for visualising high-dimensional data in a lower dimension. The beginning circumstances influence the quality of SOM learning: the initial weight of the map, the neighbourhood function, the learning rate, the sequence of training vectors, and the number of iterations (Pal & Pal, 1993). SOM was used in the current study to visualize and identify the relationship between the best predictors chosen by the best model. Figure 2.8 shows an illustration of SOM Map.

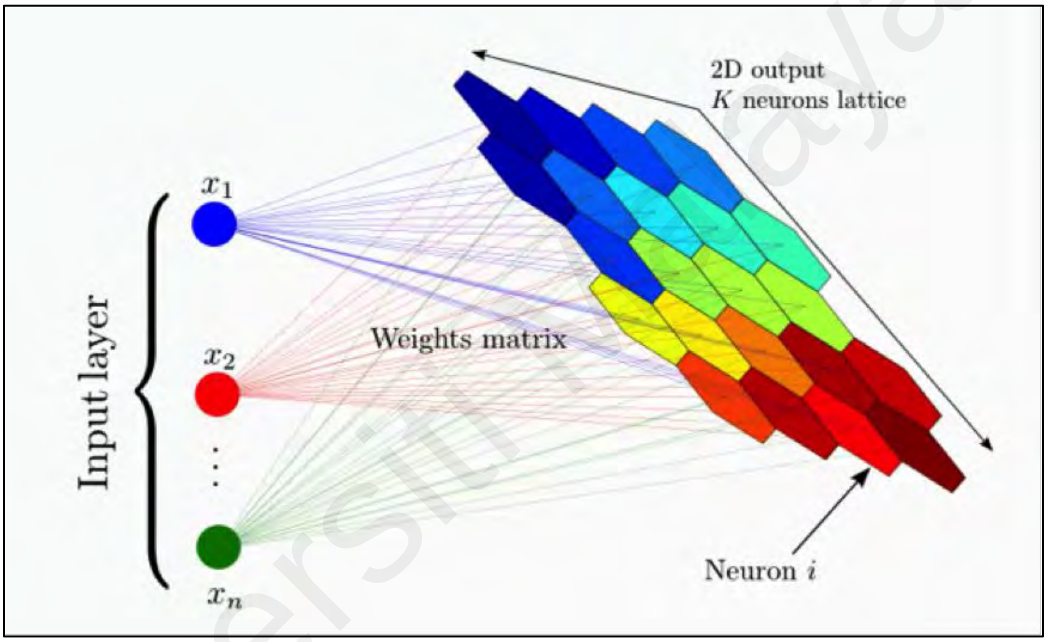
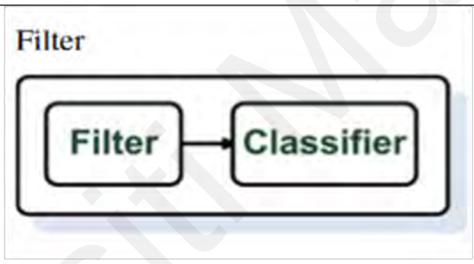
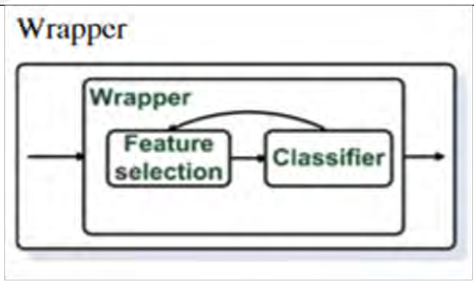
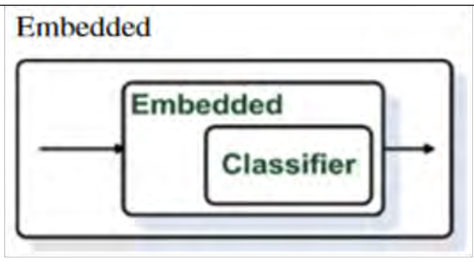


Figure 2.8: Self-Organizing Map (SOM) diagram (Pal & Pal, 1993)

2.10.3 Feature Selection

The increase in features will increase the dimensionality of data. Data with extremely high dimensionality gave serious challenges in machine learning since it caused overfitting, resulting in the performance degenerates. Therefore, to address the problem, feature selection was necessary to reduce the redundancy in data to increase the learning performance. Besides, a small subset of data will decrease the computational time and cost, making the training time faster. (Tang, Alelyani, & Liu, 2014). As table 2.5 discusses the types of feature selection.

Table 2.5: Types of Feature Selection *(Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos, 2013)*

Feature Selection	Diagram	Explanation
Filter		General characteristics of training data and carry out the feature selection process as a pre-processing step with independence of the induction algorithm.
Wrapper		Involve optimizing a predictor as a part of the selection process
Embedded		Perform feature selection in the process of training and are usually specific to given learning machines

There were three methods in feature selection as shown in Table 2.5: filter, wrapper and embedded method. The filter method is the oldest method in feature selection. The features selected were not considered from the classifier learning algorithm. The features have been selected based on the measures on general characteristics and do not rely on the learning algorithm. On the other hand, the wrapper method selected the features based on the learning algorithm. It emphasized the interaction of the classifier and its dependency among features, optimizing the feature selection. Therefore, it achieved a better performance accuracy compared to the filter method. The embedded method is a feature selection method that combines both filter and wrapped method. It overcame the shortcomings in both models which were large features of the data is used in the classifier. The method selected several subsets of the features and then compared the performance accuracy for them in order to choose the feature subset with the highest accuracy (Jain & Singh, 2018).

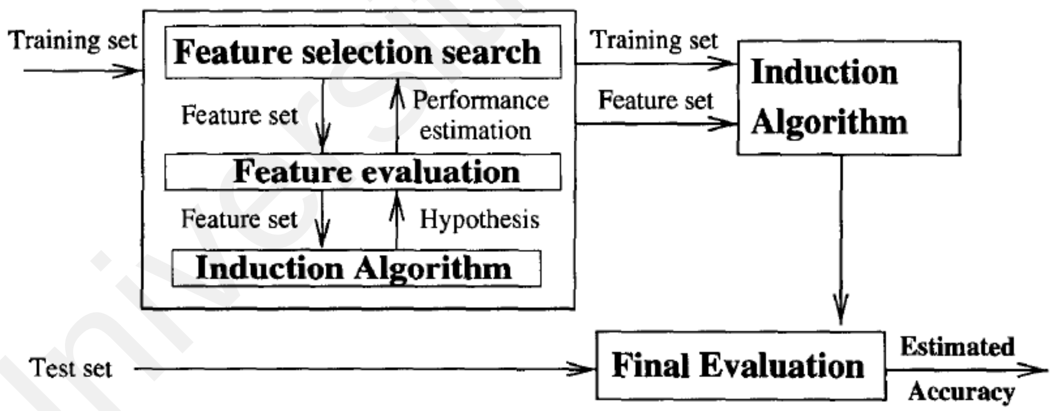


Figure 2.9: Wrapper Method

Figure 2.9 illustrates the wrapper method, it had feature subset selection that based on two algorithms: sequential selection algorithm and heuristic search algorithm. It used an induction algorithm as "black box" and searched for all parameters in the space. The induction algorithm evaluated all parameters and justified the features that will increase the model accuracy prediction and performance. The features justified will be partitioned into strongly relevant, weakly relevant and irrelevant features. Sequential selection is used to extract the strongly relevant and weakly relevant feature to get the optimal subset features as seen in figure 2.10 (Kohavi & John, 1997).

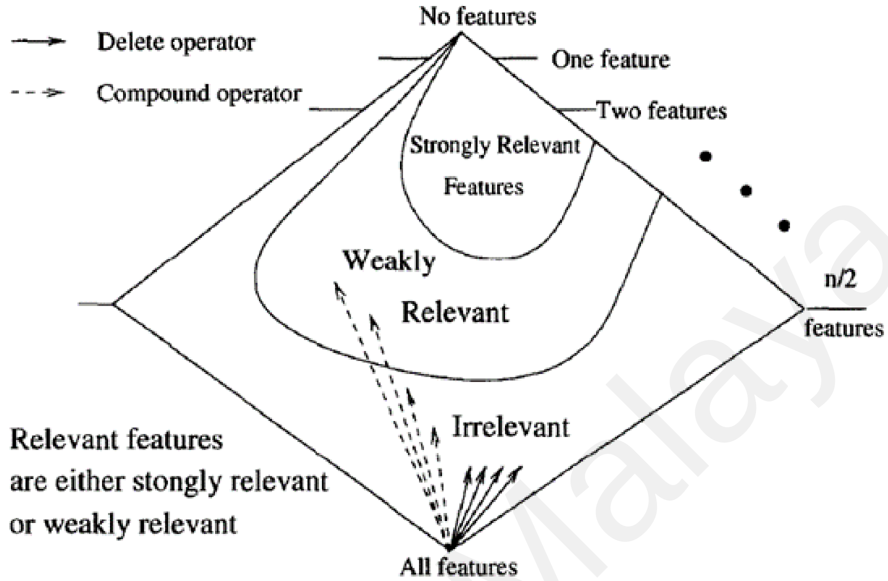


Figure 2.10: Relevant Features (Kohavi & John, 1997)

The sequential selection algorithm was then split into a sequential forward selection and sequential backward elimination. In sequential forward selection, it started from an empty set and then added features one by one according to the rank given by the objective function. The higher rank will be added first until the required number of features is satisfied. On the other hand, sequential backward elimination eliminated the features one by one from the lowest rank of features. Heuristics algorithm found the best subset features by considering chromosome bits represented in the genetic algorithm. (Chandrashekar & Sahin, 2014).

Even though the forward selection algorithm was faster, but the backward elimination algorithm minimized the loss of predictive information since it kept the conditional probability of the class from the given features as close as to the original distribution. (Koller & Sahami, 1996)(Koller & Sahami, 1996). Besides, the backward elimination method gave better performance in selecting features to predict the patients with congestive heart failure. (Narin, Isler, & Ozer, 2014).

2.10.4 Model Evaluation

In the evaluation stage, the performance metrics which is given the main priority to be considered was Area Under Curve (AUC). The study by Ling, Huang, & Zhang (2003) has proven that AUC is a better performance metrics than the accuracy to evaluate the performance of a classifier than the accuracy for balanced and imbalanced data sets, which the classifier's performance is compared across the entire range of class distributions and error costs. Consequently, by choosing the classifiers with better AUC, better ranking can be produced. Not only that, if classifiers that optimize AUC is built, such classifiers will give better AUC and accuracy (a surprising result), as compared to classifiers that optimize the accuracy.

The receiver operating characteristics (ROC) curve with larger AUC is better than that with a smaller AUC (Balakrishnan et al., 2008). Various medical studies have been using AUC in evaluating the performance of the ML models developed. For examples, the study by Balakrishnan et al. (2008) in classifying patients with or without diabetes, the study by Nanayakkara et al. (2018) in characterising risk of in-hospital mortality following cardiac arrest, and the study by Wallert et al. (2017) in predicting the two-year survival versus non-survival after first myocardial infarction using machine learning and Swedish national register data.

At the same time, performance metrics in the confusion matrix, especially the number of misclassified cases, was taken into consideration regarding the performance of a model. The lesser the number of misclassified cases, the more satisfied the model performance is. This is in corresponding to what had been done in the study by Balakrishnan, Narayanaswamy, Savarimuthu, & Samikannu (2008). In the study, it mentioned that in medical domain, it is desirable that the classifier to have predicted a healthy patient as sick, but not a sick patient as healthy, which makes the medical diagnosis a failure one. Thus, it is acceptable to sacrifice the precision of positive classifications (healthy patient cases in the study) in exchange for improving the precision of negative cases (unhealthy patient cases in the study).

Sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), McNemar's p-value and kappa of the model were considered as well. Sensitivity is defined as true positive rate whereas specificity is defined as true negative rate. Positive predictive value, the probability of patients with positive screening tests truly have a positive outcome, and as opposed for negative predictive value. The model with a higher value of kappa is considered more reliable. The higher the values, the better the performance of the model.

2.10.5 Data Preprocessing

Many factors are affecting the result of machine learning on a given task. Data Preprocessing would be conducted to generate the final training set which reduces irrelevant, redundant and unreliable data to improve the quality of the data. Data Preprocessing includes data cleaning, normalization, transformation and feature selection. Data cleaning is a process of removing instances that contains too many null values. It also considers as outliers. Data normalization and transformation is a process of scaling values within the average range. It often occurs when there has a great difference between the maximum and minimum values (Kotsiantis, Kanellopoulos, & Pintelas, 2006).

In machine learning, the preprocessing technique is used to deal with imperfect data. Supposedly, the ideal training data is complete and noise-free. However, most real-world data are far from being clean and complete. Preprocessing technique is employed to remove the noise and missing value data since they will consume more processing time and computational power to deal with the complex data. (García, Luengo, & Herrera, 2016).

Machine learning requires many methods in data pre-processing. Centering and scaling are data preprocessing forms for numerical data. Centering data across the elements of one mode then subtracts the average value from every element of a vector. On the other hand, scaling multiplies all elements in the array containing a certain variable by a constant to alter the range of data. These transformations help improve the interpretability of parameter estimates when there is interaction in the model. (Bro & Smilde, 2003).

Medical data mostly contained highly imbalanced data. Therefore, some classification method made the machines are prone to the accuracy of the majority class. Meanwhile, the high dimensional data made the situation more complicated. It is not easy to find a classifier because the classifier may overfit for the data. Therefore, preprocessed data is a direct method to overcome the effect of high dimension and imbalanced data (Yin & Gai, 2015).

However, overfitting is a common phenomenon occurred in data mining. A learning algorithm is learned from the training data and make new predictions when the new data point is applied. It aims to estimate the outcome with higher accuracy. Overfitting occurs when the algorithm identified and memorized the peculiarities in the training data rather than finding a predictive rule. Therefore, it has a negative impact when the new data point is applied. It against our objective function which is optimization by minimizing the error in prediction. The problem can be addressed by cross-validation (Dietterich, 1995)

Cross-validation is one of the methods used to overcome over-fitting. It split training data into a mini-train test set to tune the model. The standard methodology of cross-validation is k-fold cross-validation. Cross-validation is an iterative method that accesses the model performance on a given set of hyperparameter to avoid overfitting. It divided the training data into parts and recycled and reused them, untrain part was then as a test set, resulting in a set of hyperparameter.

In cross-validation, choosing a subset k number is essential because it decides how many folds divided and validate to guarantee the performance of the model. Normally, the typical value of k is 5,10 and 20 as they can apply in the large dataset and reach a general range for error estimation. Besides, by analyzing the experimental result with k value 3, it can be a good choice because it gained a tighter range for error estimation. It explained that there is not worth the meaning of error estimation in choosing the best k value, it is highly dependent on dataset given (Anguita, Ghio, Oneto, & Ridella, 2012).

2.10.6 Application of Machine Learning in Orthopaedics Studies

Machine learning classifiers utilise each patient's medical data to forecast the presence of illnesses based on hidden patterns discovered in the data. Support vector machines (SVM), Random Forests (RF), Decision Trees (DT), and Artificial Neural Networks (ANN) are the most widely utilised machine learning algorithms for analysing complicated medical data. SVM is based on mapping data to a higher dimensional space using a kernel function and selecting the maximum-margin hyper-plane that separates training data to enhance accuracy through space separation optimization. RF generates a large number of classification trees from a random subset of predictors and bootstrap samples. When compared to other techniques, RF can handle high-dimensional data in training faster.

ANN is made up of multiple layers and connections that are designed to resemble biological neural networks in order to build sophisticated classifiers. ANN has been used to solve a variety of non-linear pattern categorization challenges. DT is made up of tests or attribute nodes that are linked to two or more subtrees, as well as leafs or decision nodes that are labelled with a class that reflects the decision (Mantzaris, Anastassopoulos, & Lymberopoulos, 2008). SVM, RF, ANN, and DT are common options in medicine and bioinformatics for tasks that require choosing useful factors or genes and more correctly predicting illnesses.

Zhao et al. (2003) have used Several machine learning algorithms, including SVM, RF ANN, and logistic regression (LR), were used to estimate osteoporosis risk in postmenopausal women and quantify bone mineral density. In this study, SVM was used to screen the femoral neck in postmenopausal women and the results were compared to a traditional clinical decision tool, the osteoporosis self-assessment questionnaire (OST) (Zhao, et al., 2016). (Sapthagirivasan & Anburajan, 2013) applied SVM kernel classifier-based computer-aided diagnosis (CAD) system for osteoporotic risk detection with 90% accuracy rate. (Umadevi & Geethalakshmi, 2012) used Back Propagation Neural Network, K-Nearest Neighbour, and Support Vector Machine to identify fractures in the long bones of the tibia. SVM is also used to predict fracture risk (Cristianini & Shawe-Taylor, 2000) (Burges, 1998) and hip fracture (Cristianini & Shawe-Taylor, 2000). (Jiang, Missoum, & Chen, 2014).

Tseng (2013) discovered that ANN outperforms conditional logistic regression in an age- and gender-matched case control analysis of morbidity and death among patients with hip bone fractures. They investigated the elements that may impact hip risk and used a logistic regression model (CLR) and an ensemble artificial neural network to assess the risk (ANN). They compared the two machine learning models in order to determine the risk and variables associated with hip fractures.

Using ANN, (Shaikh et al., 2014) created an expert system for identifying and diagnosing osteoporosis. (Mantzaris, Anastassopoulos, and Lymberopoulos, 2008) accurately predicted the existence of osteoporosis using two distinct ANN techniques: Multi-Layer Perceptron (MLP) and Probabilistic Neural Network (PNN) (PNN).

The most often used machine learning approach is multilayer perceptron (MLP), a supervised ANN learning method. This method, however, gives little insight into the importance of variables in relation to the predictor. Transparency is critical in fields such as medical decision assistance. This may be accomplished through the use of classification and regression trees (Tseng, 2013). It has been utilised in the orthopaedic sector for decision analysis of surgical vs nonoperative treatment of Jones fractures. DT has been utilised in paediatric orthopaedics to establish foot disease groups and biomechanical characteristics linked to symptom on the basis of paediatric clinical data by building a decision tree prediction model. (Mantzaris, Anastassopoulos, & Lymberopoulos, 2008). RF is a machine learning approach that is a subset of bagging. The RF technique is a classification and regression approach created by (Breiman L. , 2001) that is based on the aggregate of a large number of decision trees generated using multiple bootstrap samples.

Out-of-bag (OOB) estimates of generalization error and variable importance measures are the two by-products of RF method. The RF technique has been shown to be more accurate than other supervised learning methods such as MLP and SVM. When the relationship between the response and the predictors is complex and the predictors are highly correlated, RF has been utilised in a number of applications in computational biology and medicine. In (Hasan, Islam, Samio, & Chakrabarty, 2018) research has used 10 machine learning approaches on classifying adult orthopaedic patients based on the biomechanical features, which includes Adaptive Boosting, Decision tree, Gaussian Process, K-Nearest Neighbor, Logistic Regression, Multi-Layer Perception, Naïve Bayes, Quadratic Discriminant Analysis, Support Vector Machine, and Random Forest. In their studies used six biomechanical features as parameters for the algorithm, concluded that Decision Tree has proven the most accuracy for their dataset with 620 instances which is 92%. With the high accuracy of the classification model, it may assist doctor in identifying disease in a more accurate and faster way.

According to (Chang, Hung, Hu, Lee, & Shen, 2018), data mining and machine learning techniques have proven to possess an excellent ability to construct prediction models in the medical domain and sought to develop a reliable prediction model in the near future and improve the current clinical references and making an important decision and correct judgement. Logistic Regression and Classification and Regression Tree in (Chang, Hung, Hu, Lee, & Shen, 2018)study shows the highest accuracy among the 3 datasets. However, their studies are focused on predicting the bold transfusion in orthopaedic procedures.

Another ML algorithm which is known as XGBoost algorithm is used in orthopaedic disease studies and has a high accuracy and recall rate. Besides in comparison of running time of the three different models, XGBoost proof that it has a clear advantage in running speed (Li & Zhang, 2019). However, XGBoost ML algorithm is not applied in our study is because it only yields one outcome, as dealing with patients, other suggestion should consider as well. Besides, the data type and parameter setting does not favour this algorithm.

Studies from (Mantzaris, Anastassopoulos, & Lymberopoulos, 2008), (Yu, Ye, & Xiang, 2016) and (Grigsby, Kooken, & Hershberger, 1994) also focused on applying

ML methods to improve the diagnostic rate and reduce the doctor workload. Thus, it is proven that an ML with high accuracy able to help doctors and specialist in making a better decision, however, the medical field is wide and a specific system is needed to assist the specialist in their diagnostic. The table 2.6 summarized previous studies related to the application of ML in the adult orthopaedic field.

The ML technique has been used in a variety of orthopaedic studies. However, there are relatively few research that examine ML in the field of orthopaedics, particularly among children, since the therapy for adults and children differs. In our earlier work, we used machine learning approaches such as ANN and RF to estimate fracture healing time in the paediatric orthopaedic discipline (Malek S. , et al., 2016). This study uses RF and SOM in examining the lower limb fracture healing time and the algorithm is utilised in the present study together with new algorithm developed for upper limb fracture.

Previous research has estimated paediatric fracture healing time using supervised and unsupervised ANNs. This research used Multilayer perceptron (MLP) using back-propagation for supervised ANN and Kohonen self-organizing feature map (SOM) used for the unsupervised learning (Malek S. , et al., 2016). SOM usage also has been stated in investigation of osteoporosis dataset (Kilmer et al., 1997). To categorise the dataset for the problem of osteoporosis categorization of high and low osteoporosis risk, the SOM technique was employed. SOM is a fantastic technique for visualising high-dimensional data (Kohonen, 1988). SOM reduces the dimensionality of high-complexity data and shows data similarities using the clustering approach (Hollmen, 1996). However, the use of SVM, ANN, RF, and SOM in orthopaedics, particularly in paediatric orthopaedics, has yet to be documented, which is the goal of this work.

Table 2.6: Machine Learning (ML) in Orthopaedics Field

Authors (References)	Application	Methods	Instances	Feature Selected	Results
(Hasan, Islam, Samio, & Chakrabarty, 2018)	A Machine Learning Approach on Classifying Orthopaedic Patients Based on Their Biomechanical Features	• Adaptive Boosting • Decision tree • Gaussian Process • K-Nearest Neighbour • Logistic Regression • Multi-Layer Perception • Naïve Bayes • Quadratic Discriminant Analysis • Support Vector Machine • Random Forest	620 instances	pelvic incidence, pelvic tilt numeric, lumber lordosis angle, sacral slope, pelvic radius and degree spondylolisthesis	• Adaptive Boosting (84%) • Decision tree (92%) • Gaussian Process (89%) • K-Nearest Neighbour (90%) • Logistic Regression (86%) • Multi-Layer Perception (75%) • Naïve Bayes (85%) • Quadratic Discriminant Analysis (88%) • Support Vector Machine (89%) • Random Forest (90%) •

(Chang, Hung, Hu, Lee, & Shen, 2018)	Prediction of Preoperative Blood Preparation for Orthopaedic Surgery Patients: A Supervised Learning Approach	• Support Vector Machine • Decision Tree • Classification and regression tree • Logistic Regression	1396 patients	Demographic, Body Checkup, Laboratory, Surgery, and History. Data mining software WEKA 3.6.11 and three correlation-based feature subset selection	• Support Vector Machine (71.1%) • Decision Tree (72.2%) • Classification and regression tree (73.1%) • Logistic Regression (72.2%)
(Li & Zhang, 2019)	Research on orthopaedic auxiliary classification and prediction model based on XGBoost algorithm	• Random Forest • Associated classification • XGBoost	150 cases	Basic personal information, disease examination and laboratory information, and medication information	• Random Forest (64.5%) • Associated classification (73.7%) • XGBoost (95.1%)
(Grigsby, Kooken, & Hershberger, 1994)	Simulated neural networks to predict outcomes, costs, and length of stay among orthopaedic rehabilitation patients	• Back-Propagation Network • Compute Regression • Multiple regression	387 Patients (ages 60 - 89)	Several Orthopaedic diagnoses, age, demographic information, individual admission rating	• Back-Propagation Network (86%) • Compute Regression (81%) • Multiple regression (71%)
(Yu, Ye, & Xiang, 2016)	Application of artificial neural network in the	• ANN • Logistic	119 Patients	X-ray characteristics, Specific rating method, age, gender, bone mineral	• ANN (95%) • Logistic Regression

	diagnostic system of osteoporosis	Regression		density (BMD), alkaline phosphatase blood calcium and blood phosphorus	(87%)
(Mantzaris, Anastassopoulos, & Lymberopoulos, 2008)	Medical disease prediction using Artificial Neural Networks	• Multilayer perceptrons (MLPs) • Probabilistic Neural Network	3426 cases	Age, Sex, Height, Weight	• Multilayer perceptrons (MLPs) • Probabilistic Neural Network PNNs outperform to MLPs, they proved as appropriate computation intelligence technique for osteoporosis risk factor prediction.

2.11 Expert System

There are many different sorts of information systems, and each one is created for a certain purpose. In this study, Our major emphasis has been paediatric orthopaedics, and we have created an Expert System that applies decision-making skills to address a specific, organised problem.

An expert system, also known as a knowledge-based system, solves issues and makes recommendations using artificial intelligence (AI) reasoning techniques. Furthermore, it efficiently collects and utilises the expertise of a human expert or experts for the purpose of resolving a specific problem faced by an organisation. An expert system picks the optimum answer to a problem or a certain category of issues, and we developed an expert system that could solve and help doctors and orthopaedic specialists.

The knowledge base, an inference engine that connects the user to the system by processing queries using languages like structured query language (SQL), and the user interface are the essential components of an expert system. Expert expertise is captured by knowledge engineers, who create a computer system that contains this expert knowledge, and then apply it (Kendall, et al., 2002). Figure 2.11 shows the expert system architecture.

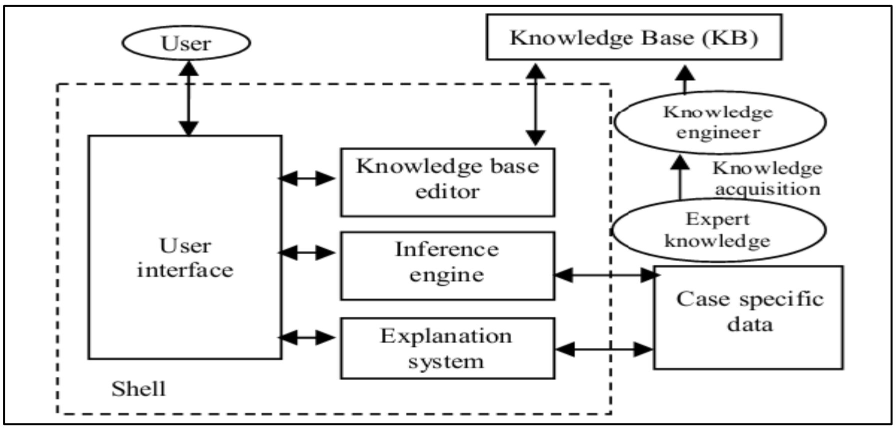


Figure 2.11: Expert System Architecture (Kendall, et al., 2002)

2.11.1 Knowledge Rule-Based Expert System

Our research incorporates the prediction of healing rate among pediatric into the rule-based expert system. According to (Abraham, 2005), it is the most basic kind of artificial intelligence, in which information is encoded into the system using rules as the knowledge representation. For our research, experts' information from doctors and orthopaedists is gathered and coded into a paediatric orthopaedic system, which can replicate the reasoning of a human expert (orthopaedict specialist) to solve a knowledge-intensive problem.

For our study, where the knowledge of paediatric orthopaedic is acquired and integrated, knowledge-based expert systems gathers tiny pieces of human expertise into a knowledge base, which is utilised to reason through a problem. The advantages of the knowledge rule-based expert system able to capture and preserve irreplaceble human experiences, reduce the number of human expertise needed, especially in emergency situations, and solutions can be produce faster than human expert.

The goal of the expert system is to transform knowledge from a human expert into a set of hardcoded rules that can be applied to the incoming information. The rules are typically conditional statements in their most basic form (if a, then do x, else if b, then do y) (Grosan & Abraham, 2011). It consists of a set of "if-then" rules that incorporate a set of facts, as well as an evaluator who monitors the rules.

In rule-based systems, there are two types of inference engines: forward chaining and backward chaining systems. The primary facts are processed first in a forward chaining system, and then the rules are used to generate new conclusions based on those facts. The hypothesis (or solution/goal) we're aiming to attain is processed first in a backward chaining system, and we keep looking for rules that will enable us to conclude that hypothesis. Backward chaining systems are goal-driven, whereas forward chaining systems are largely data-driven. The forward chaining method is especially useful in circumstances when data collection is costly yet there are few of them. (Grosan & Abraham, 2011). The inference engines used in the system for our study is the forward chining system, starting with the patient age, follow by the fracture information, by selecting the bone involved, then bone segment and fracture morphology.

2.11.2 Examples of Information System Related to Orthopaedics Studies

Osteoporosis Advisor (OPAD)

Various information systems has been developed to solve specific problems in the medical field. (Halldorsson, et al., 2015) have designed an Expert System – The Osteoporosis Advisor (OPAD) could assist in osteoporosis diagnosis and therapy. A knowledge mapping approach is used in the system's design. Expert clinicians were interviewed to establish the clinically relevant factors for osteoporosis therapy and bone mineral density (BMD) assessment recommendations.

OPAD was created out of a concerned that clinicians would have trouble understanding the risk value number for each patient and providing particular diagnostic and preventive and treatment recommendations based on worldwide guidelines and expertise. In addition, OPAD provides an interactive viscometer that allows users to compare their results to the general population of the same gender and age. For busy practice physicians and other health care practitioners, including nurses working in fracture liaison services, OPAD allows "best practise" in osteoporosis risk evaluation of fragility fractures and treatment to be documented, communicated, and automated in a simple bedside manner. However, the OPAD system is presented in Swedish data. Figure 2.12 below illustrates the system userinterface available for the Osteoporosis Risk Calculator.

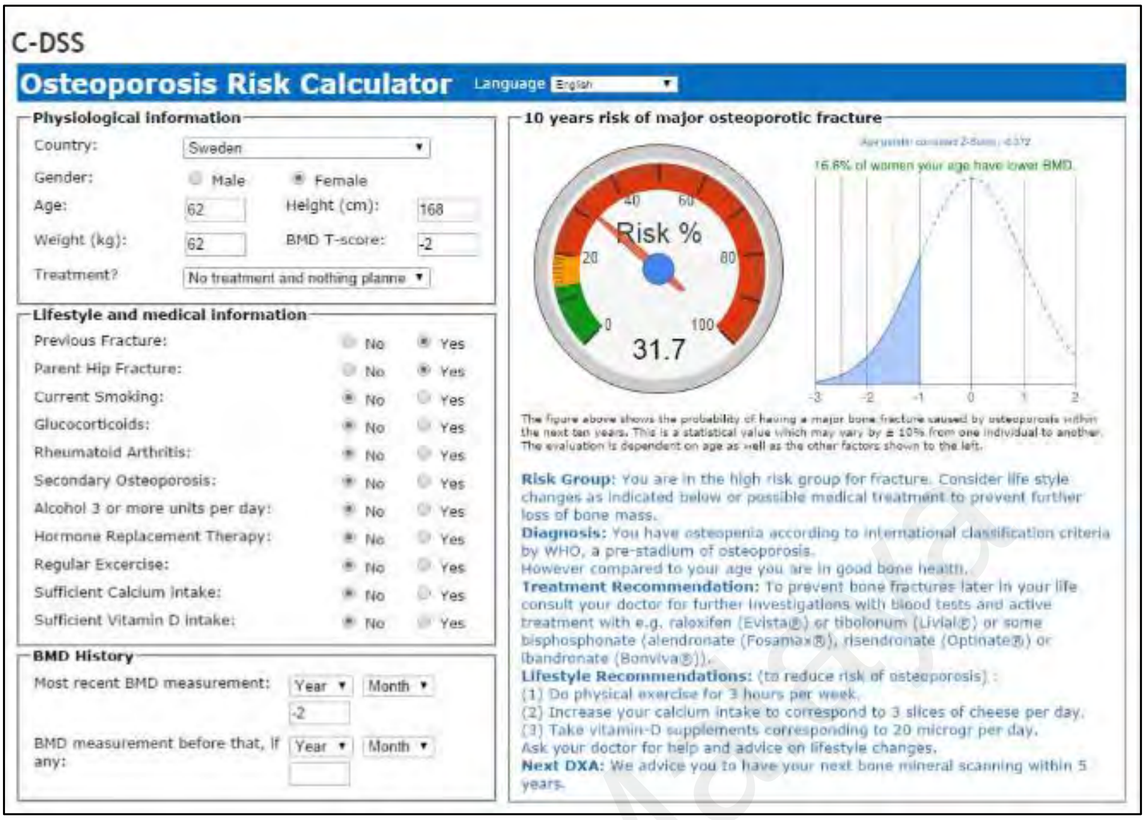


Figure 2.12: OPAD Osteoporosis Risk Calculator (Halldorsson, et al., 2015)

Vertebral Compression Fractures Decision Support Tool

By using Magnetic Resonance Imaging (MRI) Feature Analysis, Wang et al. (2011) created an online evidence-based decision support system for differentiating benign from malignant vertebral compression fractures (VCF). A feature checklist with an image gallery built from verified reference instances, a prediction model, and a reporting mechanism compose up the system. Users can enter case results to be interpreted using a structured feature checklist on the website. For clarity and training reasons, the visual gallery supplements the checklist. A logistic regression prediction model is then used to assess the likelihood of malignancy using the data from the checklist.

The report wording is standardised and highlights the important positive and negative results. This computer-assisted diagnosis system illustrates how diagnostic decision assistance may help radiologists in three areas: First, through feature checklists and illustrative picture galleries, in image interpretation; second, through feature-based prediction modelling; and finally, through structured reporting.

The Hypertext Markup Language (HTML) and JavaScript are used to implement the system on the web. A feature checklist is provided in HTML, and the ML Algorithm is implemented on the webpage using JavaScript. The web-based implementation of this prediction model for VCF analysis by combining peer-reviewed literature, book chapters and local experts and it is available at http://bricweb.partners.org/vcf.

(Wang, Jeanmenne, Weber, Thawait, & Carrino, 2011) said that the use of evidence-based medicine is increasing, particularly in radiology, and that the Decision Support Tool is an essential tool for advancing evidence-based radiology, formalising and standardising image interpretation, and communicating outcomes. The figures below (Figure 2.13, 2.14, 2.15 and 2.16) shows screenshots of of the webpage.

Figure 2.13: The primary screen of the vertebral compression fracture decision support website presents a feature checklist to the user. The majority of these features are dichotomous in nature, shown as checkboxes. A few are non-dichotomous discrete variables, shown as pop-up menus. (Wang, Jeanmenne, Weber, Thawait, & Carrino, 2011)

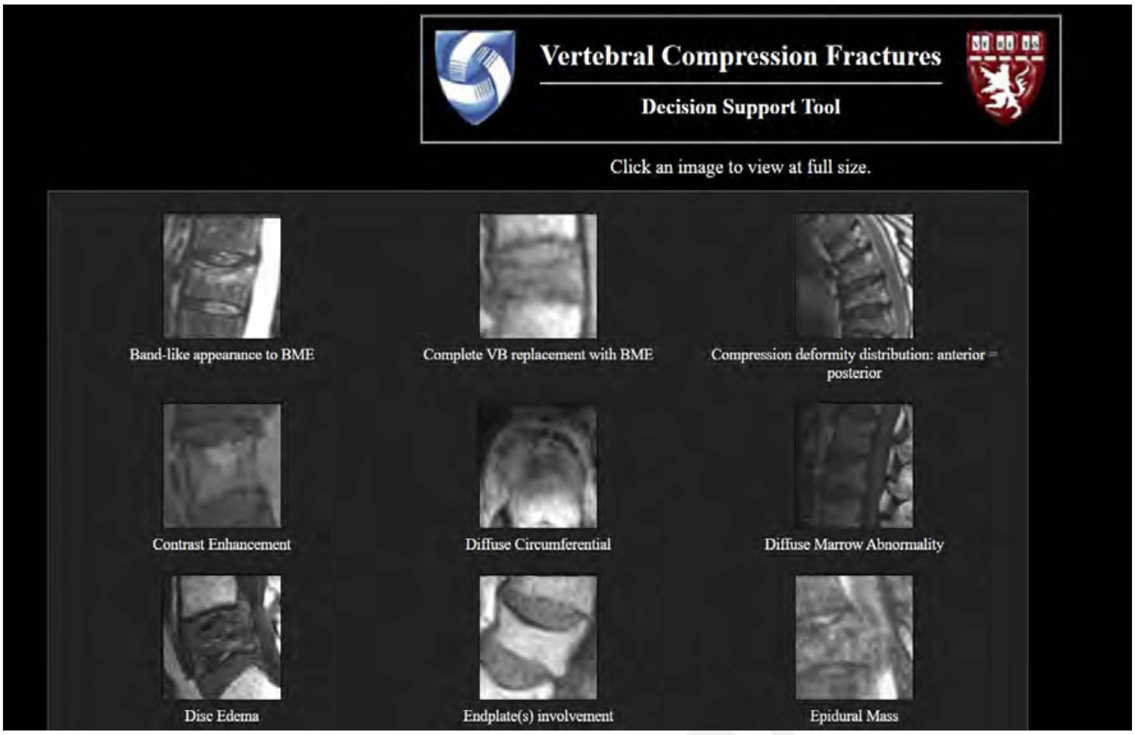


Figure 2.14: MRI features of vertebral compression fractures are illustrated using series of images. These may be browsed in a gallery format, accessed using the "image gallery" link toward the top of the main page (Wang, Jeanmenne, Weber, Thawait, & Carrino, 2011).

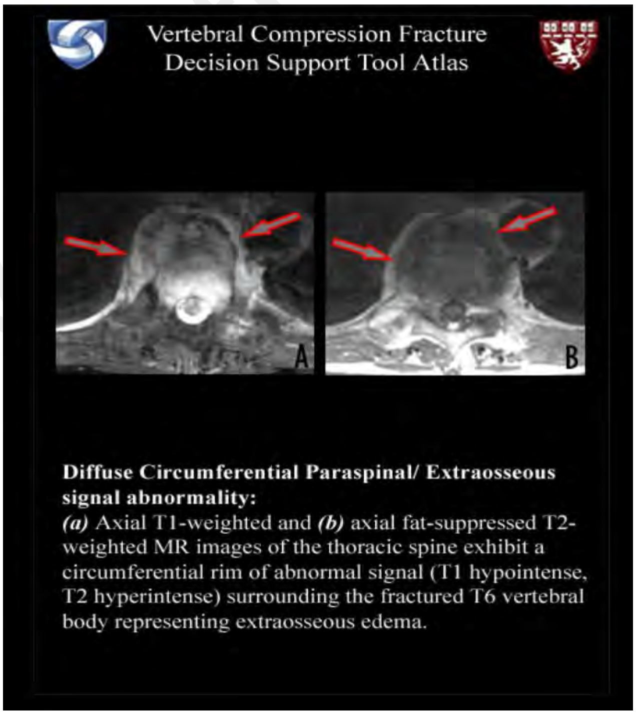


Figure 2.15: A detailed, annotated image or set of images is available for each of the MRI features listed in the checklist of the main page. A combination of image marks and text-based explanations summarize the findings which constitute a given feature, promoting a uniform understanding of these features and providing

a learning resource for trainees (Wang, Jeanmenne, Weber, Thawait, & Carrino, 2011).

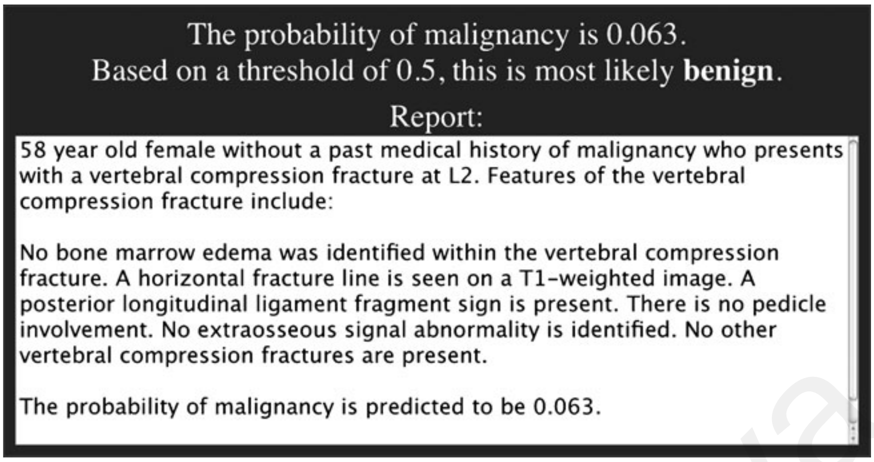


Figure 2.16: Once the feature checklist has been completed, clicking the "submit" button towards the bottom of the main page triggers the prediction model probability calculation and template-based report text generation, both shown below the checklist items. These results are displayed respectively as a probability of malignancy and as a block of text available for cut-and-paste incorporation into the user's reporting system (Wang, Jeanmenne, Weber, Thawait, & Carrino, 2011).

AO PCCF Classification System

As the fractures in children differ from adult fractures, the AO Paediatric Comprehensive Classification of Long-Bone Fractures (PCCF) which developed by the AO Foundation to classify fractures, especially for children. AO PCCF is a derivative from a systematic, comprehensive fracture classification system; the AO/OTA Classification of Fractures and Dislocations (previously known as the Müller/AO Classification). AO PCCF follows closely the AO/OTA fractures classifications' criteria and terminology while adding child-specific relevant fracture features (Marsh, et al., 2007). AO PCCF underwent 3 research phases to validate the system (Audigé, Hunter, Weinberg, Magidson, & Slongo, 2004).

The fracture location and morphology are included in the categorization system. The long bones and their segments are linked to the fracture location. Then, it narrows down the location by further describing the fracture subsegment. As for the fracture morphology, It is initially characterised using the location-specific child code, then a severity code, and, if available, an additional code for the displacement of unique fractures. The bones and segments are coded similarly as Müller AO Classification which has 1 as Humerus and 2 for Radius/Ulna while for the segments 1 represents proximal, 2 is for diaphyseal and 3 is for distal (Slongo & Audigé, 2007). For the subsegments, the original classification of A, B and C is replaced with D for diaphysis, M for metaphysis and E for epiphysis. Using the complete code from AO PCCF, the fracture pattern and its details can be identified. According to (Marsh, et al., 2007) (Audigé, Hunter, Weinberg, Magidson, & Slongo, 2004), epimetaphyseal subsegments from segments 1 and 3 and shaft fractures from segment 2 are listed as the most frequent subsegment fracture in paediatric cases. Please refer figure 2.17 below of the AO PCCF Classification System.

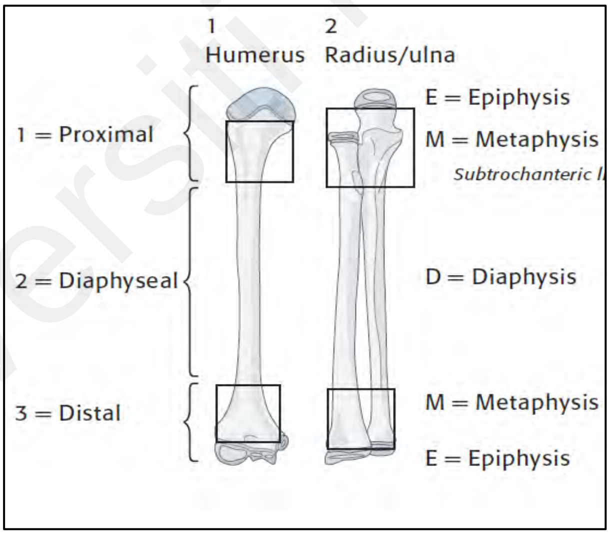


Figure 2.17: AO PcCF Classification System

AO Surgery References

The AO group is a medically directed and research organisation that specialises in the surgical treatment of trauma and musculoskeletal problems while also fostering excellence in patient care and results (AO Group, n.d.). However, this AO Surgery Reference does not include a decision support function, the system only serves as a guide to medical practitioners to select the fracture type based on the guidelines provided

AO Group (n.d.) has developed AO Surgery References which is a tool for managing fractures that is based on current clinical concepts, methods, and evidence. This Classification system structure is based on the location of the fracture and also its morphology and can be accessed through this link: https://surgeryreference.aofoundation.org/. Figures including figure 2.18, 2.19, 2.20 and 2.21 shown below are the images of the user interface from AO Surgery References along with the explanation in the caption of each images.

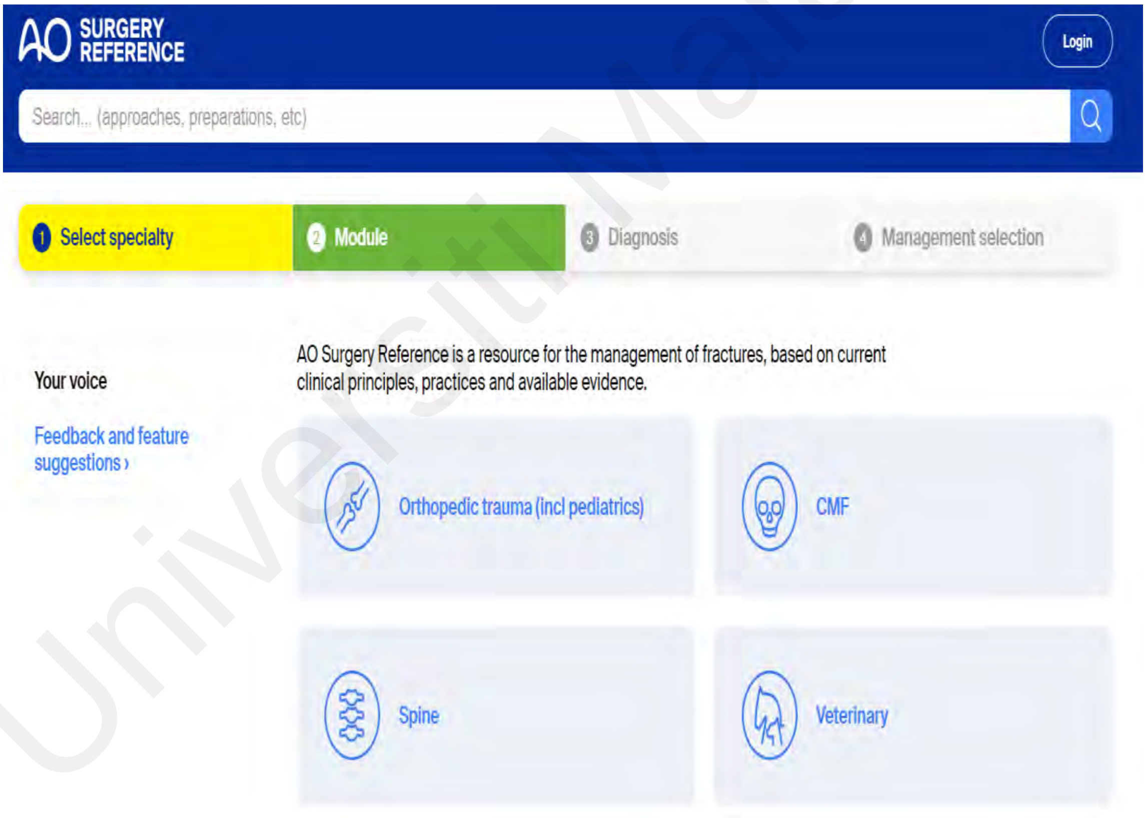


Figure 2.18: Under "Select Specialty" tab, users are allowed to choose which management of fractures they interested in, including Orthopaedic trauma (incl. paediatrics), CMF, Spine, and Veterinary.

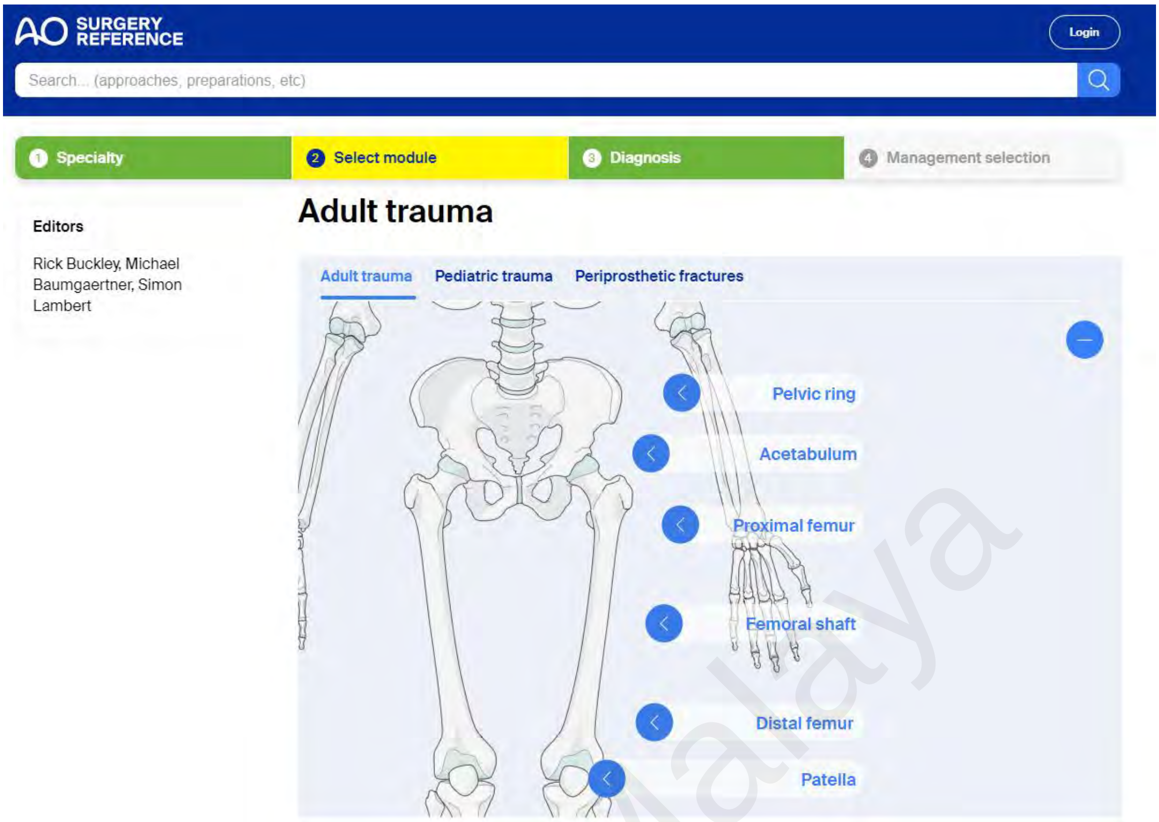


Figure 2.19: After selecting the management fractures that the user interested in, it will automatically move to the second tab "Select Module". Under Orthopaedic Management, it includes three traumas, which are Adult trauma, paediatric trauma and periprosthetic fractures.

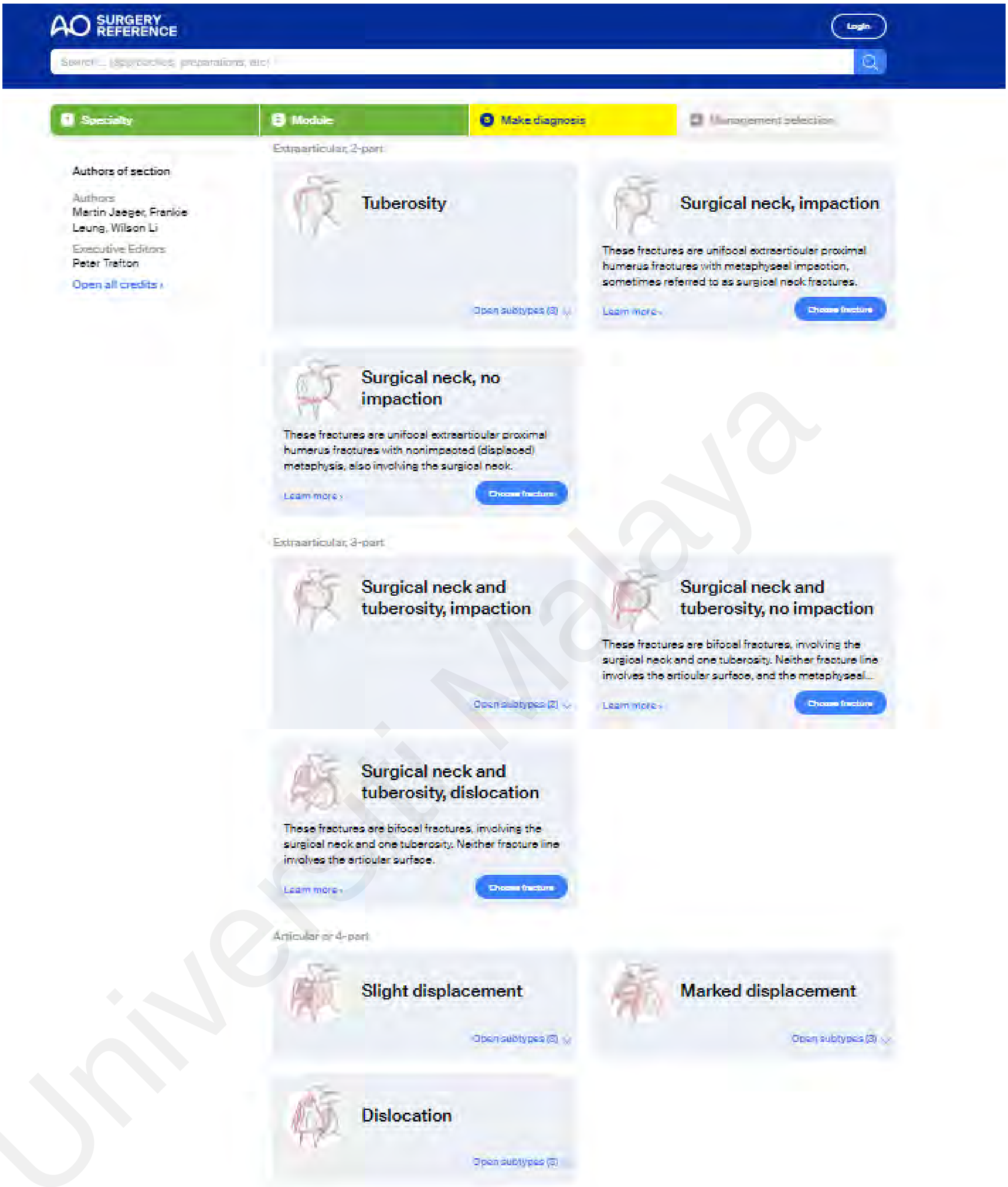


Figure 2.20: The third tab is the "Make Diagnosis" tab that users have to select one of the diagnoses then only the system will proceed to the fourth tab, which is the "Select Management" tab.

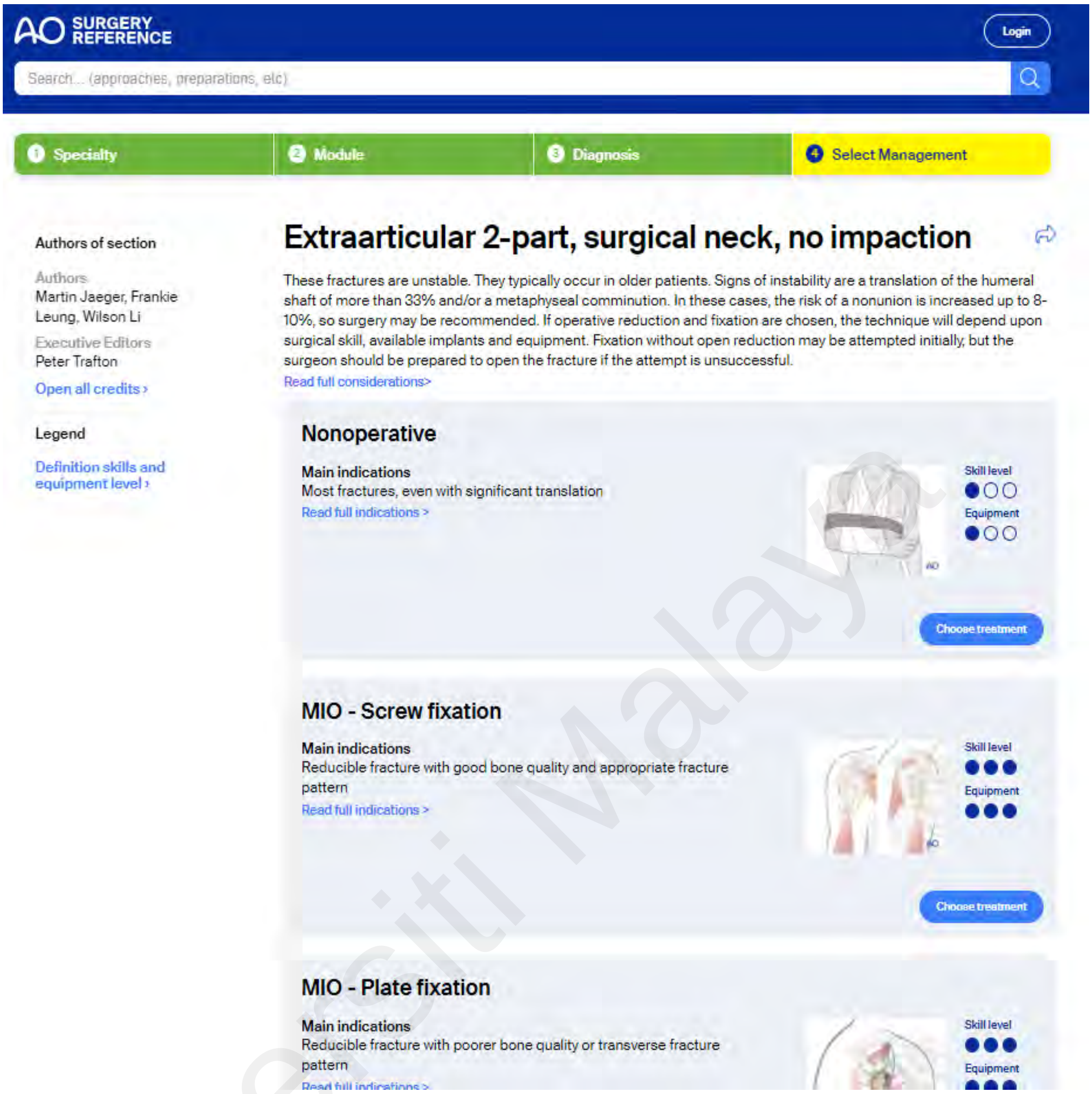


Figure 2.21: The "Select Management" tab allows the users to choose suggested management and treatment to be applied to the patients after all the criteria selected from the previous tab and it will give the best suggestions and advice to the users.

Table 2.7: Summary of Information System related to Orthopaedics Study

Information System	Website Link	Advantages	Disadvantages
Osteoporosis Advisor (OPAD)	Not available	- Gives specific diagnosis and treatment option. - User interaction is available (riskometer) - Risk Evaluation - Cost effective in fracture liaison services	- Not available online - Represent Swedish data - Only specific dataset available for certain nationality - Focused on osteoporosis patients - Does not include prediction element
Vertebral Compression Fractures Decision Support Tool	http://bricweb.partners.org/vcf/	- Feature-based prediction modeling - Image interpretation guidance - Standardized reporting - Image Galleries - Easily accessible	- Focused on Vertebral Compression Fractures through MRI Analysis.
AO PCCF Classification System	https://surgeryreference.aofoundation.org/orthopaedic-trauma/paediatric-trauma	- Easily accessible - Resources are up to date - User friendly with great interface.	- Does not include prediction element

AO Surgery References	https://surgeryreference.aofoundation.org/	- Easily accessible - Full with resources including the management of fractures - Updated with current clinical principles, practices and available evidence - Provide relevant information for clinical practitioners	- Does not include prediction element - The user has to determine fracture type based on the guide provided

CHAPTER 3 - MATERIALS AND METHODS

3.1 Data Collection and Analysis

In this study, we are focusing on the upper limb as the lower algorithms have been developed and published in previous work (Malek S. , et al., 2018). The Paediatric Orthopedic Unit, University Malaya Medical Centre, Kuala Lumpur, Malaysia, provided us with 242 upper limb patient data and radiographs from the years 2010, 2014, 2015, and 2017. Radiographs of fractured bones (humerus, radius and ulna) from infants and young children of ages less than 12 years were included, with ages recorded from the time of initial injury. Variables such as the segment and section of the bone involved, the kind of bone fracture, and measurement data such as the angulation of the fracture and fracture lengths to the physis in both anterior and lateral views are collected from patient records examinations (Malone, Sauer, & Fenton, 2011). We also determined the period between damage and bone union, as well as the patient's age and gender. The time in which the bone achieved union was defined as healing time.

A total of 11 input variables is used in this study; five continuous variables and six categorical variables. Categorical variables are explained in table 1. The healing time which measured in weeks is the output variable for this study. For continuous variables, the findings are given as mean and SD, whereas for categorical variables, the results are expressed as frequencies. As shown in tables 3.1 and 3.2, correlation analysis was used to find the significant association between variables.

Table 3.1: Summary Statistics of the Upper Limb Data

Variables	Attributes	Total (242)	p-Value
Age		8.7 ± 3.4	0.418
Gender	Male	196 (81.3)	0.474
	Female	45 (18.7)	
Anterior diameter		39.7 ± 35.5	0.001
Anterior angulation		5.8 ± 7.9	0.581
Lateral diameter		40.3 ± 35.6	0.001
Lateral angulation		10.6 ± 13.3	0.009
Bone involved	Humerus	8 (3.3)	0.339
	Radius/Ulna	233 (96.7)	
Bone part	Proximal	12 (5.0)	<0.001
	Diaphyseal	88 (36.5)	
	Distal	141 (58.5)	
Bone segment	Epiphysis	17 (7.1)	0.003
	Metaphysis	132 (54.8)	
	Diaphysis	92 (38.2)	
Fracture type	Transverse	129 (53.5)	0.269
	Spiral	13 (5.4)	
	Torus	69 (28.6)	
	Wedge	15 (6.2)	
	Greenstick	15 (6.2)	
Fracture Severity	Simple	235 (97.5)	0.711
	Multifragmentery	6 (2.5)	

Table 3.2: Summary of Categorical Variables for Upper Limb Data

Variables	*Categories*
Type of Fracture	*(1=Transverse, 2=Spiral, 3=Torus, 4=Wedge, 5=Greenstick)*
Bone Involved	*(1=Humerus, 2=Radius/Ulna)*
Gender	*(1=Male, 2=Female)*
Bone Part	*(1=Proximal, 2=Diaphyseal, 3=Diaphysis)*
Bone Segment	*(1=Epiphysis, 2=Metaphysis, 3=Diaphysis)*
Fracture Severity	*(1=Simple, 2=Multi-fragmentery)*

3.2 Algorithm Steps

Several steps were taken to develop the best model that can be integrated into the system. The workflow can be viewed as follows as illustrated in figure 3.1.

Figure 3.1: Workflow of Machine Learning Development

I) Data Pre-processing: The process of cleansing, deleting and extracting raw data to obtain the paediatrics' patients' data with the age below 12 years old. This step is necessary to remove missing values, noise and outliers in the raw dataset to obtain an accurate dataset to be applied in the model later on.

II) Data Partition: Data was split into two sets, 70% for model development and 30% for testing sets for model evaluation. To prevent overfitting during training K-fold cross-validation was used.

III) Model Development: Machine learning methods were used in this stage, are Random Forest and Support Vector Regression. Model tuning was carried out to determine the optimum number of parameters for each model. The process can be repeated manually or automatically by R. With the desired final tuning parameter, it is used to refit the model by training.

IV) Feature Selection: Backward sequential elimination method was used to identify the significant features for models. The variables will be eliminated according to the rank given on each model by using R, from the lowest rank to the highest rank. The model was retrained after each feature elimination until the final predictors were identified.

V) Performance evaluation: Evaluate the model using the testing dataset to avoid biases in results. The area under Receiver Operating Characteristic (AUROC), accuracy, confusion matrix, sensitivity, specificity are several evaluation methods to justify the model's performance. all developed models were compared to identify the final model which will be embedded into the system.

3.3 Model Development

Before model development, data were normalised as some variables have a large variation or spread. Normalization of the raw datasets was, therefore, necessary to ensure that all values of the variables are within the same range. Normalization is essential for machine learning models such as ANN and SVR (Ogasawara, et al., 2010) (Shen, et al., 2016). The normalised data is then divided randomly and stored into two separate datasets in an array; training set (70%) and testing set (30%). Then 5-fold cross-validation was used to avoid overfitting for model development on the training set (Geisser S. , 1993) which was implemented using the R caret package. Output was then de-normalized before evaluating the model performance.

Root mean square error (RMSE) was adopted in this study as a model assessment for the developed machine learning methods. RMSE was calculated based on the de-normalized value of the output. RMSE is used to measure the average level of prediction error. It indicates the absolute fit of the model to the data or how close the observed data points are to the model's predicted values (Armstrong, 2001).

Data were split into 70% for model training and 30 % for testing. Data normalisation was performed to ensure that all values of the variables are within the same range (Shen, et al., 2016). 5 – fold cross-validation was used on the training dataset as it results in a less biased or less optimistic estimate of the model performance

(Kim, Drake, & & Park, 2006). Output was then de-normalised before evaluating the model performance. Machine learning model performance assessment was carried out using Root mean square error (RMSE). RMSE was calculated based on the de-normalised value of the model output. RMSE is used to measure the average level of prediction error. It indicates the ideal fit of the model to the data or how close the observed data points are to the model's predicted values (Armstrong, 2001).

In this study, the ways to encounter overfitting and obtain better results are cross-validation and parameter tuning. Each model has an important parameter that cannot be detected by the data. Many parameters in the model used to control the complexity of the model. There is also no analytical formula available to determine an appropriate value of the parameter on each model. The only method is the tuning parameter. The general approach is to define a set of values and then generate a reliable model across them.

The Wilcoxon Signed-Rank test (Fay & Proschan, 2010) was used to compare the difference between predicted and actual healing weeks of the machine learning model.

3.4 Machine Learning Algorithm

The following machine learning algorithms have been implemented in this study focusing on upper limb fracture data among paediatric.

3.4.1 Random Forest (RF)

RF algorithm (Breiman L. , 2001) was used for fracture healing time prediction and variable selection. RF incorporates multiple binary decision trees constructed from bootstrap samples of training data and select a subset of predictors randomly at each node. The RF is repeated with different ntree argument starting from *ntree*=500 and *ntree*= 1000. This is done to examine the sensitivity to method argument mtry and ntree to better determine important variables and the stability of the variable importance scores.

Variable importance measures are automatically computed for each predictor in the RF algorithm to assess and rank the variables (Díaz-Uriarte & De Andrés, 2006). The mean decrease accuracy is defined as the difference between the out of bag error (MSE for regression) obtained through random permutation of the predictor of interest and the OOB error from the original dataset. Mean decrease accuracy was used to determine the important variables by RF algorithm (Genuer, Poggi, & Tuleau-Malot, 2010) (Archer & Kimes, 2008).

3.4.2 Support Vector Regression (SVR)

SVR is built based on the concept of Support Vector Machine (SVM). In this study, SVR is used since the response variable is numerical rather than categorical (Vapnik, Golowich, & Smola, 1997). SVR is often used in classification problems or assigning classes when the data is not linearly separable. SVR is a nonparametric technique that depends on kernel functions and uses the principle of maximal margin as a convex optimization problem. SVR uses a cost parameter to avoid over-fit. Tuning parameter 'sigma' was held constant at a value of 0.6, and the cost parameter is set to the value of C = 0.25. In this study, the constructed SVR model for prediction used Radius Basis Function (RBF) kernel and linear kernel for variable importance.

Variable importance measures for the SVR model using linear kernel are obtained by building models for every predictor variable available against the response variable (Guyon & Elisseeff, 2003). The RMSE values are then recorded and a plot of variable importance is generated. The variable which possesses the lowest RMSE is marked as the most important variable.

3.5 Feature Selection

Sequential backward elimination (SBS) was performed on the ranked variables by RF and SVR linear method. The variables were deleted in descending order iteratively (Genuer, Poggi, & Tuleau-Malot, 2010). The prediction models were trained and tested for each iteration.

A variable is deemed as an important variable to the healing time if the RMSE value increases when the variable is deleted. The predictions model was constructed based on the variables that are deemed important and using a complete set of variables.

3.6 Self-Organizing Map (SOM) Development

A self-organizing map (SOM) was generated by using a toolbox in MATLAB VER. (R2013, Math Works). SOM (Kohonen, 1988) was used in this study to ordinate factors associated with fracture healing time. The Euclidian distance between the input factors is calculated and visualized as U-matrix (unified distance matrix) as a result of the trained SOM. The U-matrix represents the distance between neurons. The winning neuron is selected based on the neuron that responds greatly to a given input vector where the winning neuron and maybe its neighbour can learn by altering the weights in a way to furthermore reduce the Euclidean distance among the weight and the input vector via the equation.

SOM decreases data dimensions and plot similarity by clustering technique. The Euclidian distance between the input factors is calculated and visualized as a U-matrix (unified distance matrix) and component planes by SOM. A component plane illustrates the comparative values of one component of the codebook vectors and the u-matrix visualizes the distances between the codebook vectors in a two-dimensional map (Kohonen, 1988). The SOM colours represent the values of umatrix elements. Light areas signify clusters and dark areas as cluster separators in SOM umatrix (Stefanovic & Kurasova, 2011). The quality of the SOM map is evaluated using topological and quantization error.

We constructed the SOM using variables selected from the best model. SOM algorithm implemented in this study was based on (Kohonen, 1988) and is as follows;

1. Randomly initialise all weights

2. Select input vector **x** = [x1, x2, x3, x4, x5, x6]

3. Compare **x** with weights **w** for each neuron j to determine the winner

4. Update winner so that it becomes more like **x**, together with the winner's neighbours

5. Adjust parameters: learning rate & 'neighborhood function

6. Repeat from (2) until the map has converged (i.e. no noticeable changes in the weights) or a pre-defined number of training cycles have passed.

Thus, the SOM contributes in providing a data visualization of the feature selected from random forest (RF) and support vector regression (SVR) model.

3.7 System Analysis

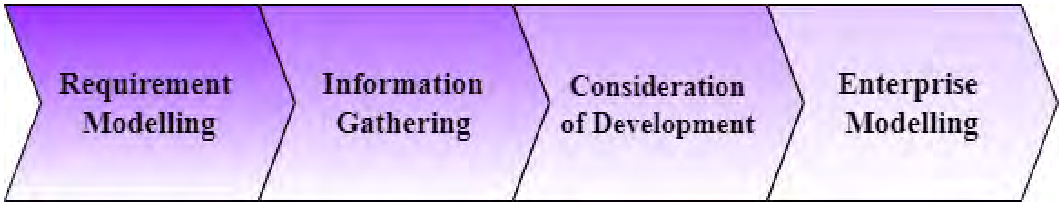


Figure 3.2: System Analysis

As illustrated in figure 3.2, there are 4 main steps in system analysis. Requirement modelling is to identify the requirements being implemented in the proposed system. The requirements include functional requirement and non-functional requirement. Requirements were identified from paediatric orthopaedic specialists from University Hospital. Requirements were also determined by going through existing documentation at the paediatric orthopaedic centre (refer to appendixes) and analyze similar available existing system online. Information from the requirement analysis step is converted into enterprise modelling using graphical representations that can be used to describe and visualize information about the proposed system.

We have used the orthopaedic system such as OPAD, AO Trauma Surgery Reference (refer to Chapter 2 section 2.11.1 Examples of Information System Related to Orthopaedic Study) as a guide to come up with the proposed system prototype.

3.8 Software Development Methodology

3.8.1 Expert System

We have used an expert system framework to develop the system prototype as depicted in figure 3.3 below. This paediatric orthopaedic fracture healing prediction system was developed for non-operated fractures where operated fractures were excluded.

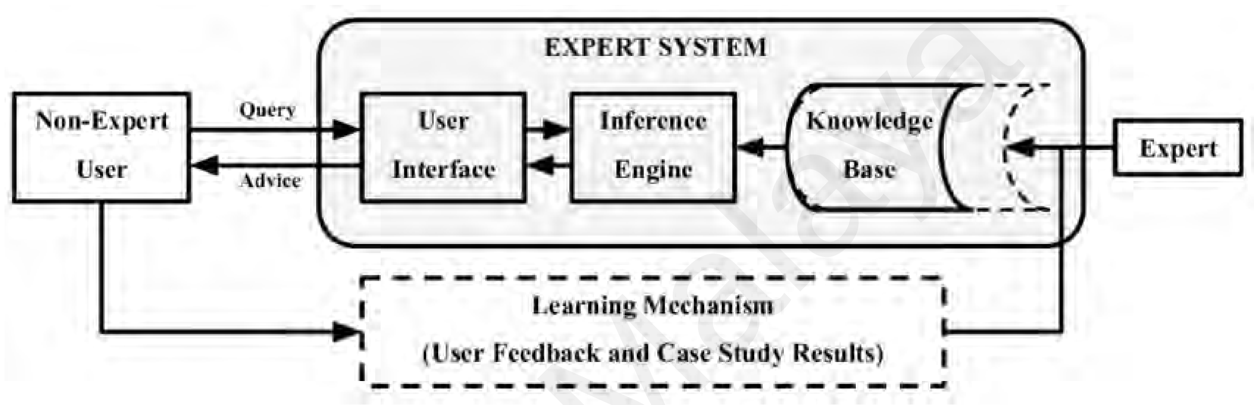


Figure 3.3: Expert System Architecture

An expert system consists of three main components:

1. Knowledge base
2. Inference Engine
3. User Interface

The expert system is designed to manage within paediatric orthopaedic knowledge, facts and rule. The component the consists of all the experts' knowledge is known as knowledge base. Next, a set of action is executed in th inference engine component if the information provided by the users fulfills meets the conditions in the rules. The thirs component is the user interface, where it offers communication between non-expert users, users are require to enter data, so that the logical process are able to start in the inference engine component.

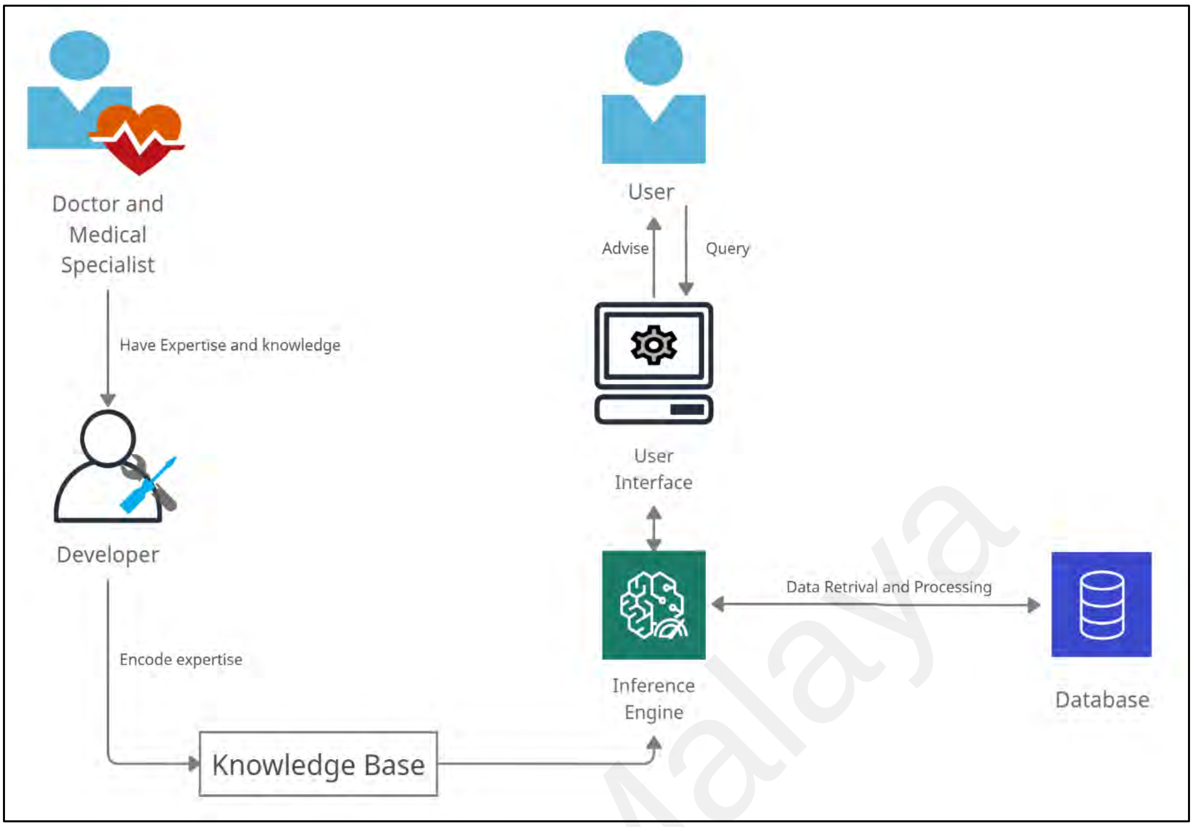


Figure 3.4: Expert System Architecture for Paediatric Orthopaedic Expert System Prototype

Figure 3.4 displays the Expert System Architecture for Pediatric Orthopedic Fracture Prediction System Prototype. The inference engine in this study consists of a trained machine learning algorithm for lower limb prediction algorithm adopted from our previous study by (Malek S. , et al., 2018), a trained upper limb algorithm in this study and expert knowledge. Expert knowledges are suggestions and knowledge gathered from the paediatric orthopaedic specialist and related documents on fracture management and healing. Inference engine executes the action whereby the user performs query through the user interface, the knowledge base will retrieve and process data from the knowledge base and pass to the inference engine. The inference engine will start the logical process and answer the user query. The existing system reported in literature are decision-support information system, and it does not include a machine learning module that performs prediction using the patient data like in this study.

Furthermore available system on orthopaedic is too general and does not focus on paediatric patients. The proposed system in this study will also include the following three modules as listed below: A login module to allow only registered user to use the system. This is to ensure the security aspects of the user information into the user account.

I. An Update view and delete the patient's demographic and previous data record module.

II. A module to calculate and display the healing time of fracture of paediatric patients and to identify the fracture type with the after guide.

3.8.2 Requirement Analysis

This section involves functional requirement and non-functional requirement in the developed system.

Functional Requirement

A functional requirement describes the components and functions of the proposed system determined after extensive fact findings. The functional requirements of the proposed system are as follows:

i. User Login Page: Existing users (medical practitioners) are required to log in and signup for the new user in the proposed system. nformation of each user and the prediction result of a patient are considered private and secure and can only be accessed by the system administrator.

ii. Machine Learning Model Calculator Page: Users are required to enter the patients' information and their medical record to predict the healing time of the fracture. The page will pass the information to the machine learning API and return the result given by the model. The page will display the predicted healing time , type and aftercare of the fracture.

iii. Patient Management Page: The page aims to manage the patients' data of the user. Users are allowed to view, delete and update the previous data record for the particular patient. Besides, users can enter the actual outcome of the particular patient in a certain timeframe.

Non-functional Requirement

Non-functional requirement describes how the system should behave. It covers everything of the system except its functionality as a functional requirement mentioned. It focuses on the attribute behaviours of the proposed system. For example, the criteria of operation like the running time and the response time on a calculation process, and the security level of data. The non-functional requirements of the proposed system involve:

i. Security: Users are required to log in before any calculations made. This ensures the patients' data on predicting the healing time of fracture are private and secure. No third party has the right to access the data.

ii. Performance: The running and response time for calculation on the proposed systemable to respone instantly when user entered the required information. .

iii. Aesthetic appeal: Menus and buttons are placed in the right position and they can be seen clearly. The operation step is simple and easy to understand and learn. Anyone is allowed to use the system since no professional knowledge is required. Image of the bone and fractures type should be available as well.

iv. Efficiently: The system targets paediatric patients in predicting the healing time of fracture among children. The prediction outcome is related to the actual following condition of the patient. This concerns the treatment and medicine that should be given to the particular patient and the expected healing time of the child patient.

3.8.3 Processed Model

The section covers all design models generated to develop the system and database. It includes a workflow diagram, data flow diagram, entity relation diagram.

3.8.3.1 Workflow Diagram

The workflow diagram visualizes the steps involved to complete the system development. It ensures the works can be accomplished smoothly. Figure 3.5 shows the workflow diagram of the development.

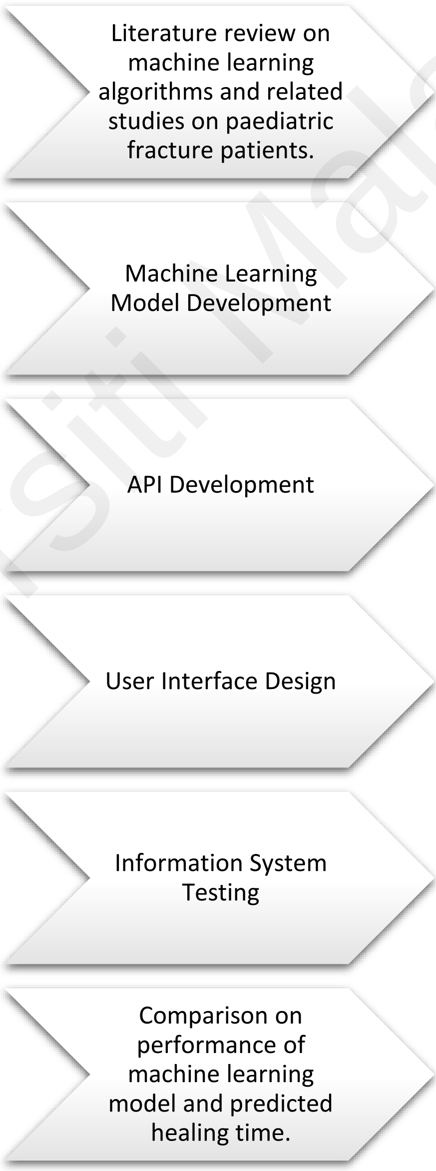


Figure 3.5: Workflow Diagram

A literature review on studies of paediatric orthopaedic patients and the application of machine learning methods for fracture healing time was done. The proposed system fracture prediction model was trained using different ML algorithms, which are RF and SVM, build on paediatric patients' fracture data. Then, API was developed using RStudio to link with the best machine learning model (SVR) identified in this study in RStudio to the system interface. A knowledge base consisting of expert knowledge, fracture type and related information and its guide is develop. The user interface was then developed to integrate the machine learning model for fracture healing time and knowledge base for fracture type identification and its after guide according to the functional and non-functional requirements as stated in the section using user interface design guideline (Booth, 2014). Testing is performed using a structured walkthrough (Yourdon, 1989) to check the system, make sure there is no coding and syntax error made during API development. Lastly, the completed system was evaluated using SUS usability matrix (Brooke, 1996) that users give subjective rating of the product usability. From the answered questionaire, each questions are converted into scores, an average score of 68 and above of SUS score could be considered as above average.

3.8.3.2 Data Flow Diagram

To depict the flow of data in the system, a context diagram and level 0 diagram is constructed and is illustrates in figure 3.6 and figure 3.7 respectively.

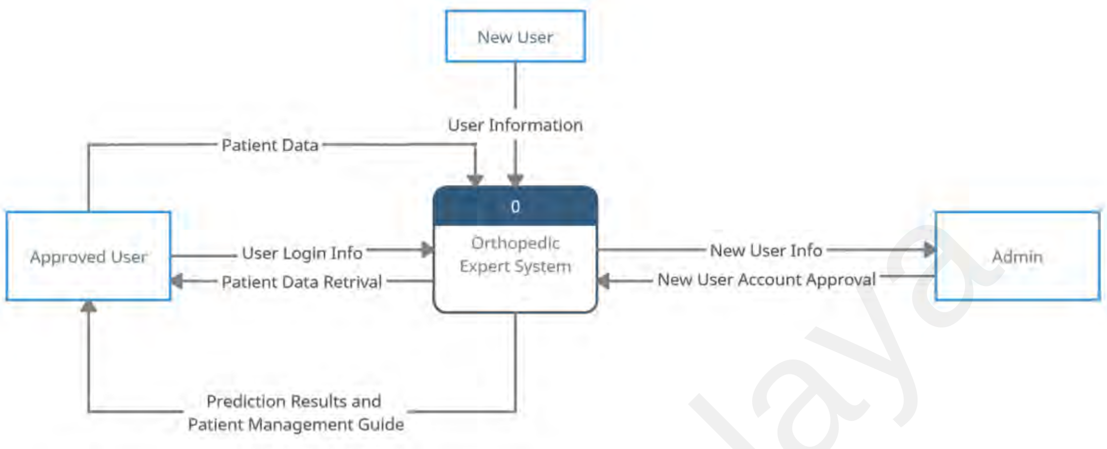


Figure 3.6: Context Diagram

Figure 3.6 is the context diagram for the system prototype. The system predicts the patient fracture healing time according to the patient data provided by the approved users, are general practitioners or junior doctors and trainee orthopaedic . New users are required to register and wait for approval by the admin then only can access the system. Apart from identifying fracture type and predicting paediatric fracture healing time, the users can manage patient's data such as add, view, update, delete and download their respective patients' data from the database in the system. The system admin can execute all the tasks accessible by the approved users and approving the newly registered users to access the system.

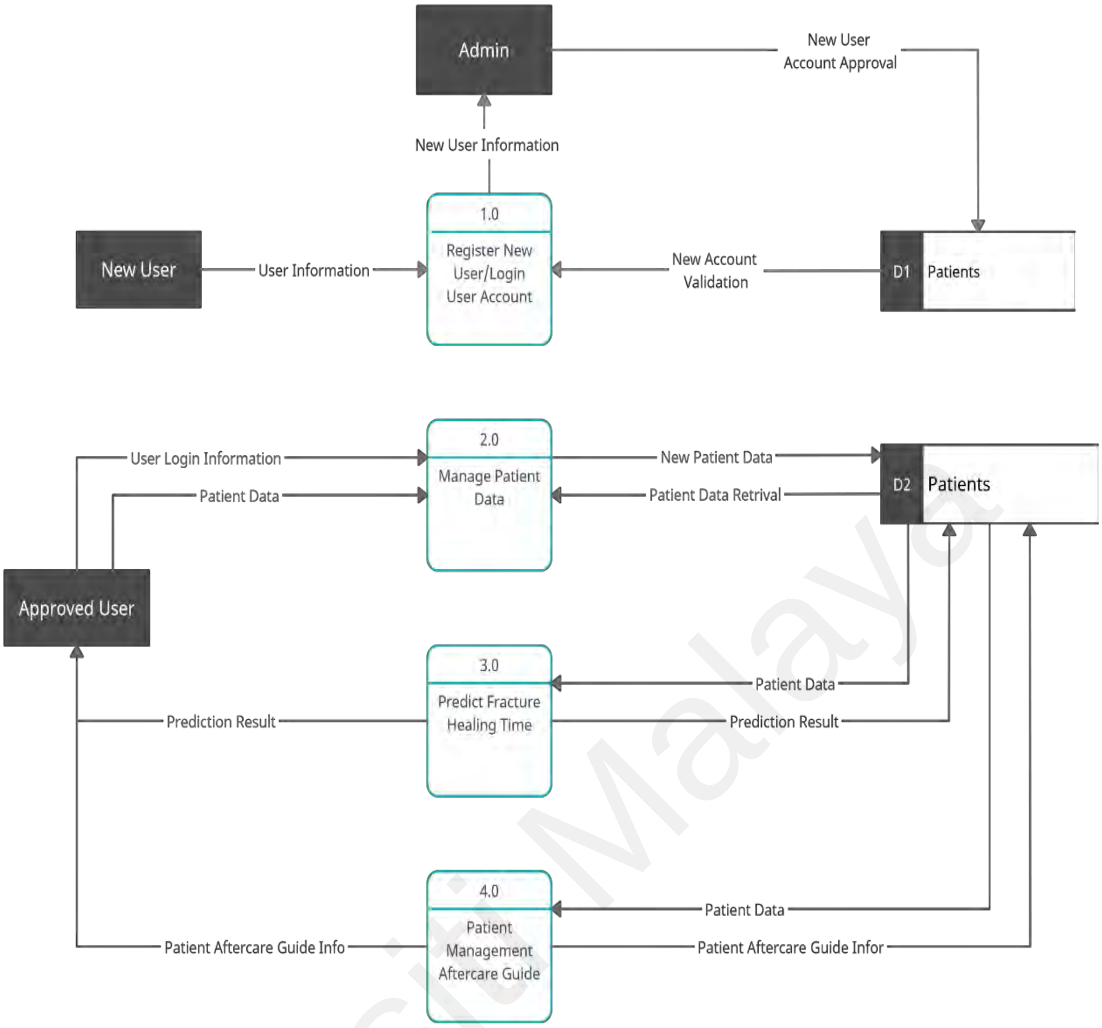


Figure 3.7: Level 0 Diagram

Level 0 diagram for Orthopaedic Expert System is illustrated in Figure 3.7. Firstly, users are required to log in to the system before using the predicting module of the system. If it is a new user and does not own an account, the new users are required to register an account and wait for system admin approval. Once new users approved by the admin are added into the 'users' table in the database.

Approved users can manage patient data, users can perform a certain function such as add, update, view, delete and download patient data. New patient data is added to the 'patient' table in the system database. Users can also update the patient's information i.e. the patient's medical history, fracture history, etc. They can also view and download patient data from the system. Next, the input data is used to predict fracture healing time, fracture type and its aftercare guide. The prediction results and the patient aftercare guide are displayed along with the patient's details, the prediction results and the patient aftercare guide are stored in the database as well.

3.8.3.3 Entity Relation Diagram

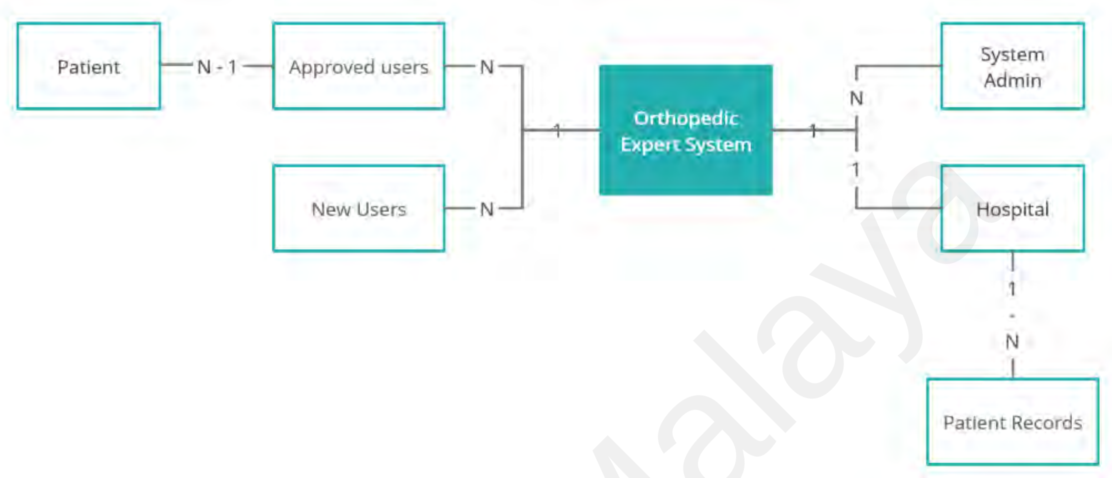


Figure 3.8: Entity Relation Diagram (ERD)

The relationship betweeen the system and the entities is illustrated in figure 3.8. This diagram is a basis for the database development of the system. The patient's details and are stored in the system to obtain the prediction results. As for the new user is required to submit their details to request approval to use the prediction calculator, then only the user can access the system. System admin can approve new user accounts and the newly registered users' information is added to the users' list in the database. Besides, the hospital can submit patient records into the system as well, so that the user can view the prediction results.

3.8.3.4 Database Schema

Case
Date Entry
Date Injury
Time Injury
Hospital Name
Place Incident
Road Incident
Previous Fracture
Previous Fracture Desc
Medical History
Surface of Impact
Mechanism of Injury
Witness
Witness Description
Bone Involved
Segment of Bone
Fracture Morphology
Anterior-posterior (AP) View Angulation
Lateral View Angulation
Fracture Distance to Physis
Patient_ID(PK)

Patient
Name
IC Number
Gender
Father Education
Father Occupation
Mother Education
Mother Occupation
Patient_ID(PK)
ID

User
ID
Email
Password
Access Level
Last updated
Date

Organization
Organization
Hospital
Verfication

Figure 3.9: Proposed Database Schema

Four tables are proposed for the orthopaedic expert system database to hold patient's information, as shown in the figure 3.9 above. "PK" stands for the primary key, while the letter in BOLD is the index key. The table 'Case' stores the patient fracture details inputted by the user. The prediction results and any updates on patients' real-time outcome after a certain time frame (if any). The 'Patient' table stores basic information of the patient including the name, identity number, parents' education and occupation. The 'User' table, with the primary key 'ID' holds the user data, whether they are approved to use the system, and their respective access level (admin or normal user). The 'organization' table stores the list of organizations that are accessible to the proposed system.

3.8.4 Website Wireframe

Before the expert system is built, the system wireframe is designed and prepared to give a clearer picture of the user interface. The proposed design of the web pages is shown in the figures below (3.10, 3.11, 3.12, 3.13, 3.14 and 3.15).

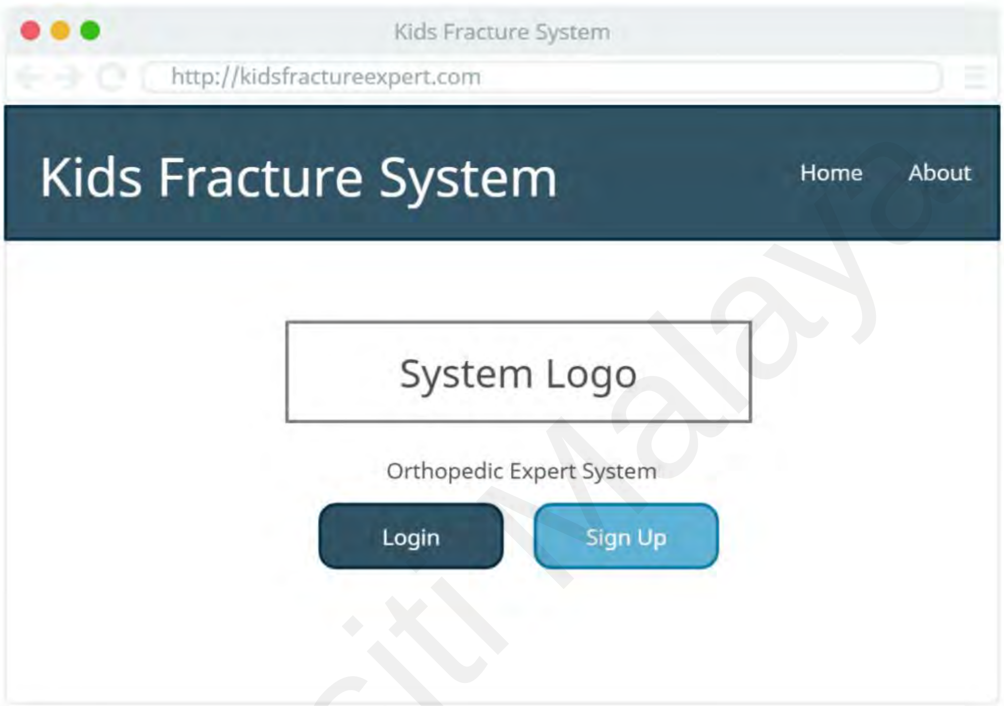


Figure 3.10: Kids Expert System Homepage Interface Design

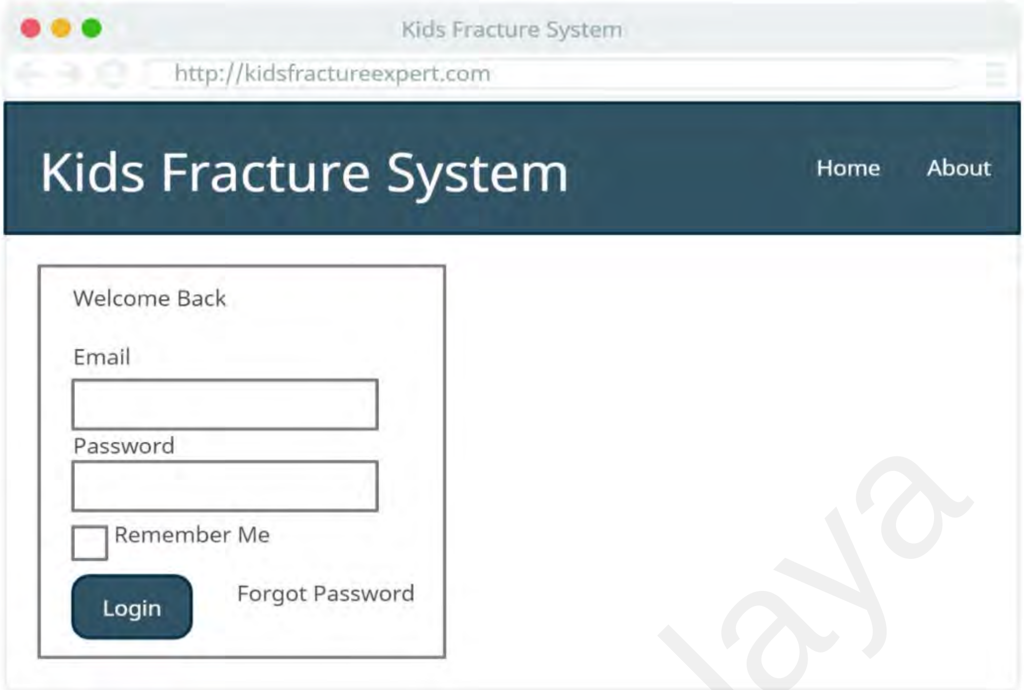


Figure 3.11: Login Page Interface

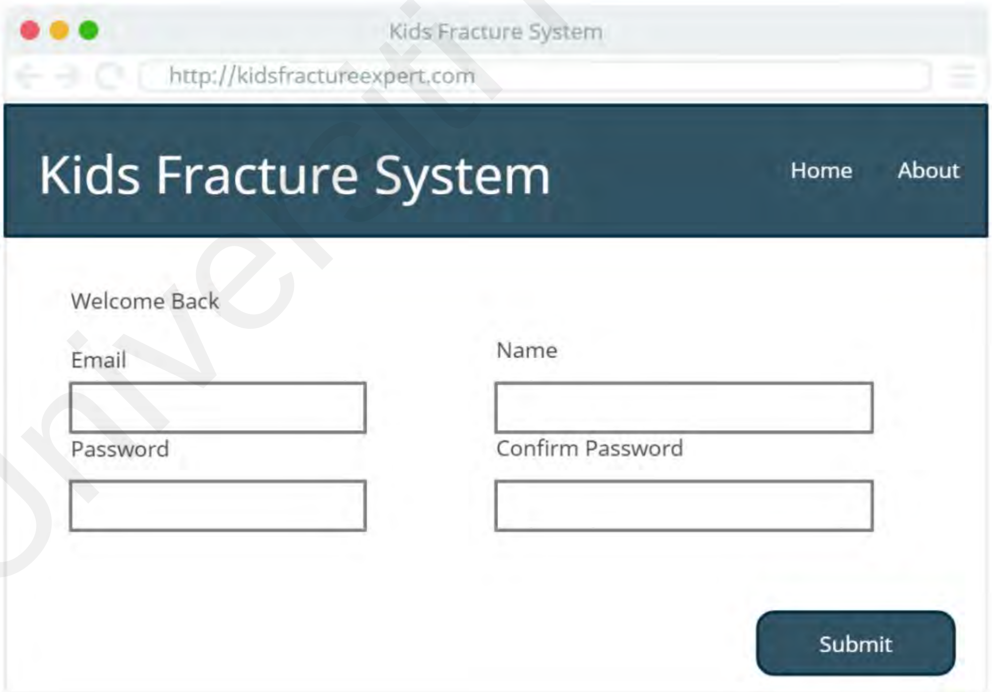


Figure 3.12: New User Registration Page Interface

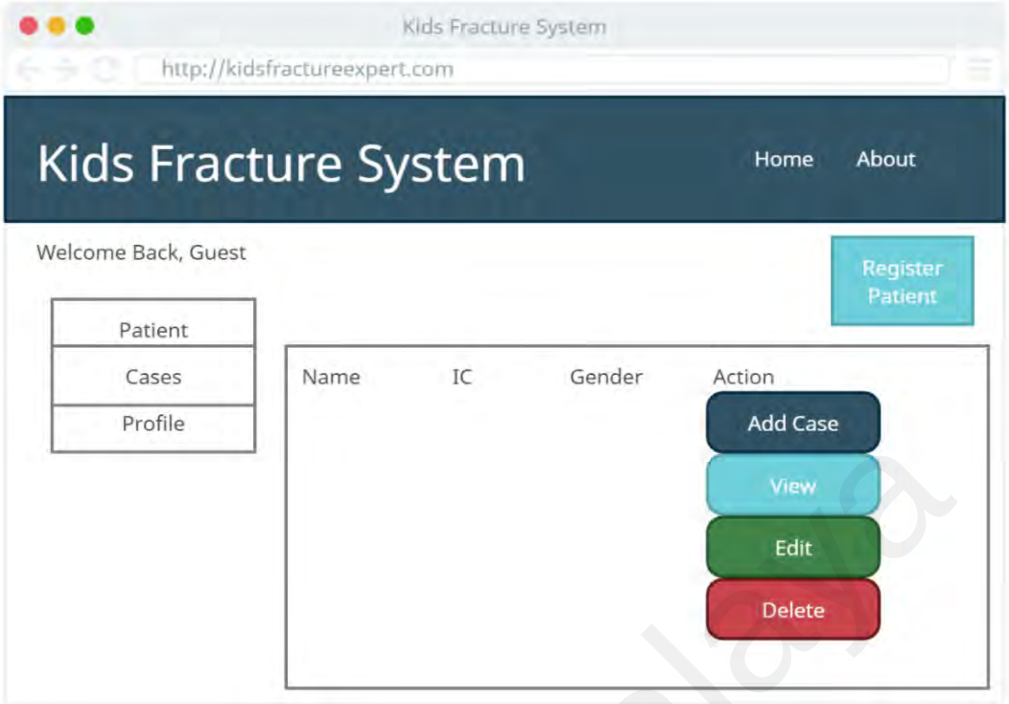


Figure 3.13: User Dashboard Interface

Figure 3.14: Predicted Result Page Interface

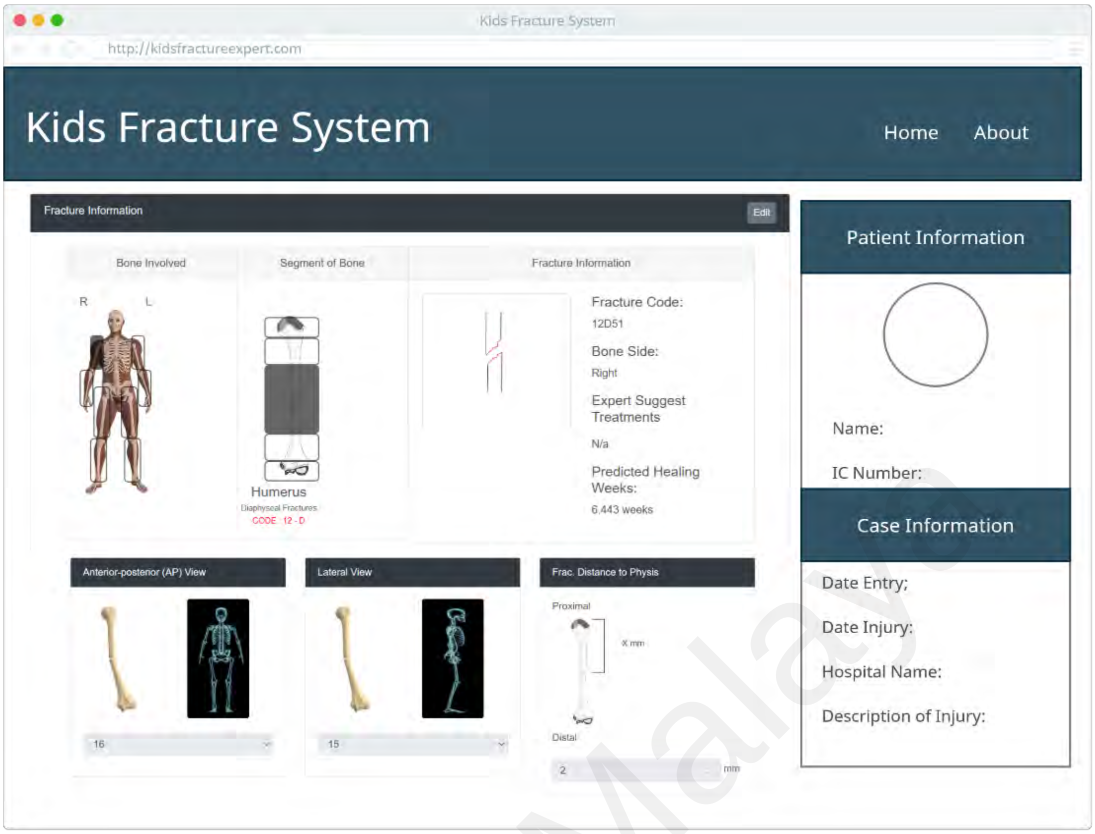


Figure 3.15: Detailed View of Patient Case with Expert Suggestions Interface

The user will first log in into the system, for new user, they are required to sign up for a new account and wait for the admin approval, the registration page for new account sign up is shown in Figure 3.12. For the existing user, they will be directed into the login page as shown in Figure 3.11 for logun into the system. Once the user successfully login into their account, Figure 3.13 is the wireframe of the dashboard, including the ‘Patient’, ‘Cases’, ‘Profile’ tab. Besides, the registered patient data are displayed on the dashboard as well. If the doctor needs to add new patient data, a ‘register new patient’ button is available the user will be directed to a page to enter the required information. The information will then be stored in the database.

Users are also able to manage their patient data, if they wish to view the predicted healing time, once the ‘view’ button is clicked, the user will be directed into the result page as shown in Figure 3.14. Besides, user able to acquire a detailed view of patient case together with the patient aftercare guide with expert suggestion as shown in Figure 3.15.

3.8.5 System Testing

System Testing is the phase of testing in the complete system. To ensure the developed system have met all design requirements, thus the "Testing" steps is mandatory. It is also to ensure the modules can be working together and interacting with other system components. Four types of testing were done which are unit testing, system testing, integration testing and acceptance testing.

(a) Unit Testing

Unit testing is to ensure the functionality of each module is correct and bug-free. Each unit of the module was tested to make sure it can function properly. Immediate action should be taken if any error is found.

(b) System Testing

System testing is carried out after unit testing. The test checks if all the modules can work together properly as a system. If an error is found, affected modules will be debugged and tested all over again. The Kids Fracture Expert is fed with input to see whether the system processes the data correctly into the correct output and the system behaves as expected.

(c) Integration Testing

The testing is to ensure the proposed system can work with the existing system without any errors occurred. The web-based fracture healing time prediction model will be integrated with the RF and SVR model in R via API. The prediction result displayed on the website should be the same as the result in R while testing. For example, one of the tested data will be entered into the system to ensure the same output was generated for both R and the system.

(d) Acceptance Testing

Acceptance testing is carried out after integration testing. The purpose of the acceptance testing is to ensure that the system meets the expectation of the user requirements, both functionally and non-functionally. Users are requested to test the completed system using the system evaluation form. Then, feedback is collected and used to correct and improve the system.

3.8.5.1 Kids Fracture Expert Test Case

Test Case is necessary and it is a sequence of steps to verify a certain feature and capability as specified by the end user. A test case includes test case ID, test case description, test data, test steps, expected result, actual result and test status. The test case able to determine a software or a system performance is functioning as per the requirements of the users (Rungta, 2021).

Table 3.3 illustrates the Test Case used in Kids Fracture Expert System to ensure the system is competent as per requirement.

Table 3.3: Kids Fracture Expert Test Case

Test Case ID	Test Scenario	Test Steps	Test Data	Expected Result	Actual Result	Test Status
#01	Check site page without Login	1. Go to site Kidsfracture expert.com. 2. Check on the user interface of the site. 3. Users able to browse through the front page of the site without login into the system.	N/A	User should able to browse through the site without login into the system	As Expected	Pass
#02	Check User	1. Go to site Kidsfracture	Email address = doctor@kidsfra	User should Login into the	As Expected	Pass

	Login with valid data	expert.com 2. Click "Login" 3. Enter email address 4. Enter password 5. Click "Submit"	ctureexpert.com Password = Ortho&321	site		
#03	Check user login without valid data	1. Go to site Kidsfracture expert.com 2. Click "Login" 3. Enter email address 4. Enter password 5. Click "Submit"	Email address = doctor@kidsfra ctureexpert.com Password = ortho123	User should not Login into the site and error message is shown	As expected	Pass
#04	Check user forgot password	1. Go to site Kidsfracture expert.com 2. Click "Login" 3. Click "Forgot Password" 4. Display "Reset Password" page 5. Enter Email Address 6. Click "Send Password Reset Link"	Email address = doctor@kidsfra ctureexpert.com	User should receive reset password email	As expected	Pass
#05	Check on the login dashboard	1. Go to site "kidsfracture expert.com" 2. Login to site	Email address = doctor@kidsfra ctureexpert.com Password = Ortho&321	User should landed at the user dashboard of KidsFractureE xpert	As expected	Pass
#06	Check on "Register Patient"	1. Login into the system 2. Click "Register Patient" 3. Enter "Patient Information" and	Patient Information Name = Brandon IC Number = 100101105785 Gender = Male Age = 10 Height (cm) = 130	User should able to registered patient and "Patient Registered" notification should appear indicates successful	As expected	Pass

		"Emergency Contact" 4. Click "Submit"	Weight (kg) = 30 Emergency Contact Name = Norman Phone = 01223225547 Relationship = father	registration		
#07	Check on "Add Case" page	1. Login into the system 2. Click on "Add Case" 3. Enter required information" 4. Enter "Submit"	Case Information Petient Name = Brandon Patient IC = 100101105785 Date Entry = 01/01/2020 Date Injury = 01/01/2020 Time Injury = 12:30 PM Hospital Name = PPUM Place Incident = Seksyen 17, PJ Road Incident = Jalan 17/1 Previous Fracture = N/A Previous Fracture Description = N/A Medical History = N/A Surface Impact = water-cement Mechanism of Injury = Deceleration trauma Witness = Father Witness Description = Playing basketball and falls off Fractire Information Bone Involved	User able to create patient case sucessfully and summary of added case is shown together with predicted healing weeks	As expected	Pass

			= Right hand, lower limb Segment of Bone = Radius (Diaphyseal Fractures, Code: 22 – D) Fracture Morphology = Simple Fragmentary (Dode: 22-D/1.1) Anterior-posterior (AP) view = 4° Lateral View = 3° Fracture Distance to Physis = 1mm			
#08	Check on "View" button	1. Login into the system 2. Click "View"	N/A	User able to view patient information.	As expected	Pass
#09	Check on "Edit" button	1. Login into the system 2. Click "Edit"	N/A	Edit Patient is loaded and user able to update patient information	As expected	Pass
#10	Check "Delete" button	1. Login into the system 2. Click "Delete" 3. Confirmation Pop Up window appear. 4. Click "OK"	N/A	User able to delete patient data	As expected	Pass
#11	Check "Cases" tab	1. Login into the system. 2. Click "Cases" tab	N/A	User able to view added cases and the predicted healing weeks	As expected	Pass
#12	Check "Profile" tab	1. Login into the system 2. Click on "Profille" tab 3. Edit Profile 4. Click "Save"	Doctor Name = Lau Email = lau1213@pantaihospital.com Hospital = Pantai Hospital, KL Doctor Registration	User able to update their profile	As expected	Pass

			Number = 123456			
#13	Check on "About" tab	1. Login into the system 2. Click on "About" tab	N/A	User able to view details and explanation of the system clearly	As expected	Pass
#14	Check"Log out"	1. Login into the system. 2. Click "Logout"	Email address = doctor@kidsfractureexpert.com Password = ortho&123	User able to logout successfully	As expected	Pass

3.8.5.2 System Usability Scale (SUS)

The System Usability Scale (SUS) developed by John Brooke in 1986 is used as the acceptance test for our expert system prototype - Kids Fracture Expert. It is a "quick and dirty" methods, low-cost assessments, fast and reliable to measure the usability in the system which only comprises 10 questions.

The SUS consists only of 10 questions as proposed by (Brooke, 1996) which are scored on a 5-point scale of the strength of agreement. The range goes from "strongly agree' to 'strongly disagree" and because the statements fluctuate between positive and negative, additional attention must be used when responding to the survey..

The SUS results are discussed in Chapter 4 – Result and Discussion. The sample questionnaire is included in appendix section. Table 3.4 illustrates the comparison of the original SUS questionnaire from (Brooke, 1996) and the modified SUS statements which are included in the acceptance testing.

Table 3.4: The original SUS statements by (Brooke, 1996) and edited statements.

Original SUS Statements	Edited SUS Statements
I think that I would like to use this system frequently	I think that I would like to use doctor@kidsfractureexpert.com frequently
I found the system unnecessarily complex	I found doctor@kidsfractureexpert.com is unnecessarily complex
I thought the system was easy to use	I thought doctor@kidsfractureexpert.com was easy to use
I think that I would need the support of a technical person to be able to use this system	I think I would need the support of a technical person to be able to use doctor@kidsfractureexpert.com
I found that the various functions in this system were well integrated	I found the various functions in doctor@kidsfractureexpert.com were well integrated
I thought that there was too much inconsistency in this system	I thought there was too much inconsistency in doctor@kidsfractureexpert.com
I would be imaging that most people would learn to use this system very quickly	I would imagine that most people would learn to use doctor@kidsfractureexpert.com very quickly
I found the system very cumbersome to use	I found doctor@kidsfractureexpert.com very cumbersome (awkward) to use
I felt very confident using the system	I felt very confident using doctor@kidsfractureexpert.com
I needed to learn a lot of things before I could get going with this system.	I needed to learn a lot of things before I could get going with doctor@kidsfractureexpert.com

The users will rank each of the questions as the following.

Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
1	2	3	4	5

The scores are then converting into numbers and calculate the usability score using SUS. The outcome of the calculated score is average at the SUS score of 70, consider as Good according to the SUS score shown in figure 3.16 below:

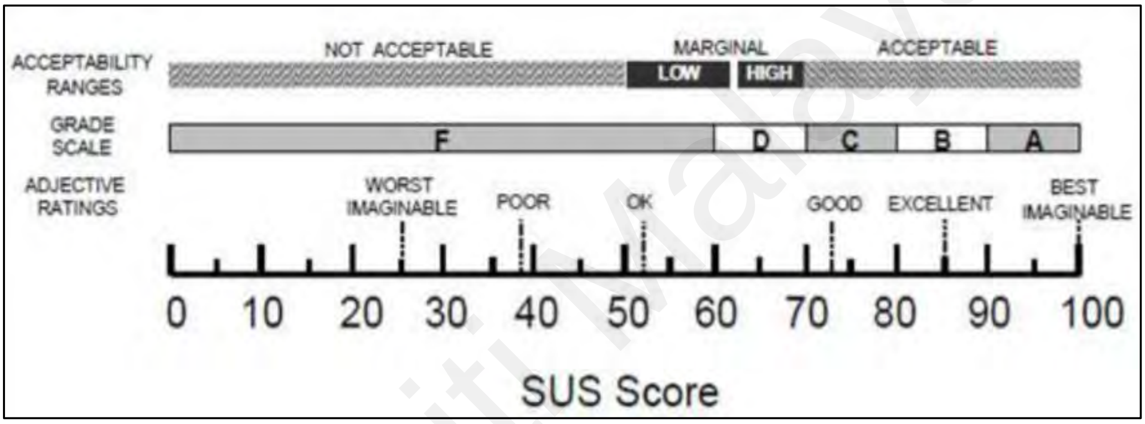


Figure 3.16: SUS scores Grade Rankings from "Determining what individual SUS scores mean: Adding an adjective rating scale." By (Bangor, Kortum, & Miller, 2009)

SUS is chosen as usability test for our study based on its wide advocacy, its quick processing time, where the respondents are able to give rapid feedback and comments, as an outcome of which the information collected is processed quickly. SUS is versatile and its wide application for various program and application system. The SUS score can be interpreted easily and improvements can be made to improve the system's performance (Bhat, 2018).

The SUS questionnaire is created using Google Form, it can be found in the link: https://forms.gle/1yEgxHwepcfQbqrg9, after the users have explore the system. For users able to view, explore and test on the system, a general username and password is given, following are the required login details.

System URL	:https://kidsfractureexpert.com/login
Username	:doctor@kidsfractureexpert.com
Password	:Ortho&321

3.8.6 Basic Requirement

(a) Hardware Requirement

The hardware used in developing the proposed machine learning model has specifications as below:

- Windows 10
- 64-bit operating system, x64-based processor
- Intel® Core™ i5-3210M CPU @ 2.50GHz
- 8.00GB RAM

480GB SSD

(b) Software Requirement

The software needed in the development of the proposed system areas listed below:

- RStudio Integrated Development for R (RStudio Team, 2019, version 1.2.1335)
- IBM SPSS Statistics 26 (SPSS Inc, 2019, Version 26.0.0)
- XAMPP (Apache Friends, 2018, version 7.4.3)
- Notepad++ (Notepad++ team, 2019, version 7.7.1)
- Microsoft Excel (Microsoft Office 365 ProPlus, Version 1908)
- Visual Studio (2017)

CHAPTER 4 - RESULTS AND DISCUSSIONS

All the outcomes obtained throughout this research will be discussed in this chapter. Fracture Healing Time Machine Learning Result and Expert System Development and evaluation. The machine learning model for the upper limb approach will be presented in this chapter. The lower limb algorithm which is published in previous work from Malek et al. (2016) will be included in the system for lower limb fracture healing time. Besides, the outcome of the web-based expert system is included in this chapter as well. We have also included the results of SUS matrixs. This paediatric othropaedic fracture prediction system is meant for non-operative fracture.

4.1 Paediatric upper limb fracture healing time prediction

Figure 4.1 illustrates the variable importance plot obtained from RF and SVR model for the variables associated with upper limb fracture healing time. The variables importance is ranked against fracture healing time. Variables with higher importance value are deemed as important in the RF model meanwhile variables that result in lower RMSE value are important in the SVR model.

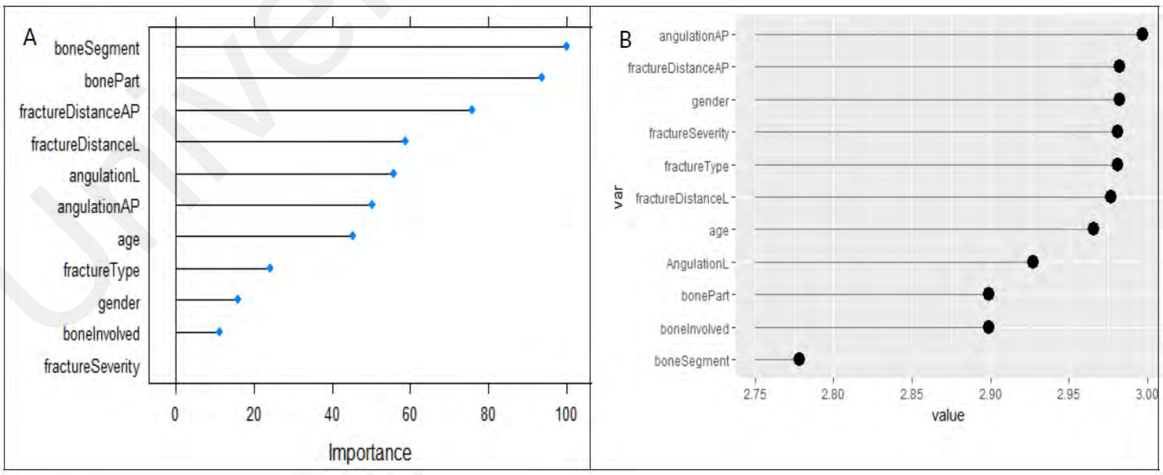


Figure 4.1: A plot of feature importance from A) RF variable importance model B) SVR variable importance model

RMSE value recorded based on ranked variables using the SBS method is illustrated in Figure 4.2 for the RF model and Figure 4.3 of the SVR model. The Higher

RMSE value recorded indicates the significance of the variable. Fracture distance and angulation, age, and the bone part where the fracture occurs are identified as important predictors to fracture healing time.

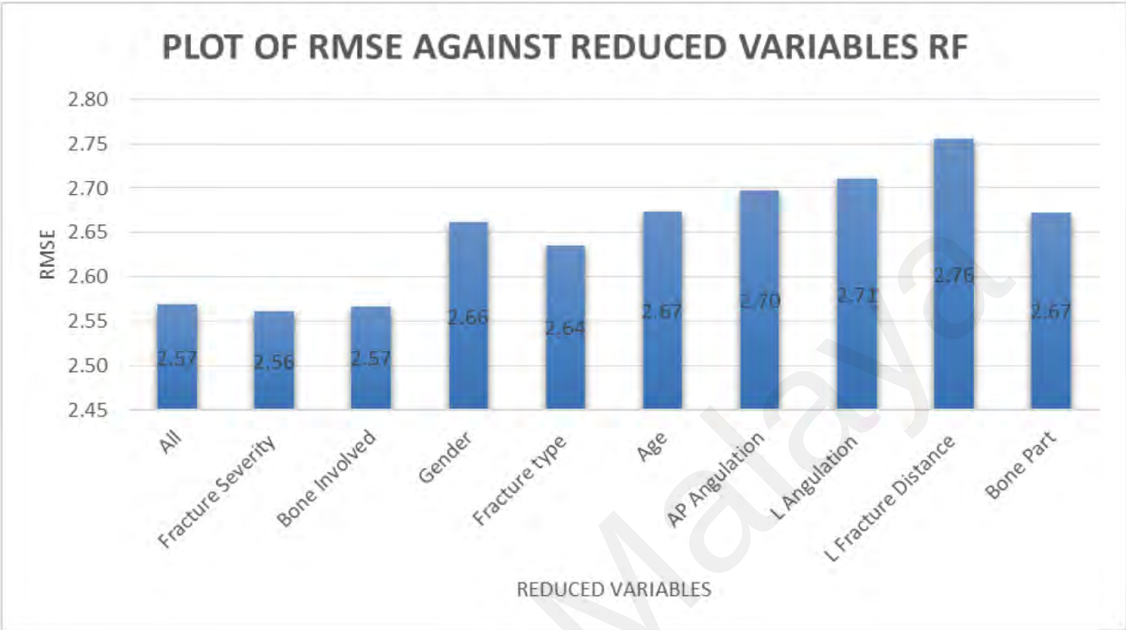


Figure 4.2: Sequential backward elimination on ranked variables based on RF variable importance method.

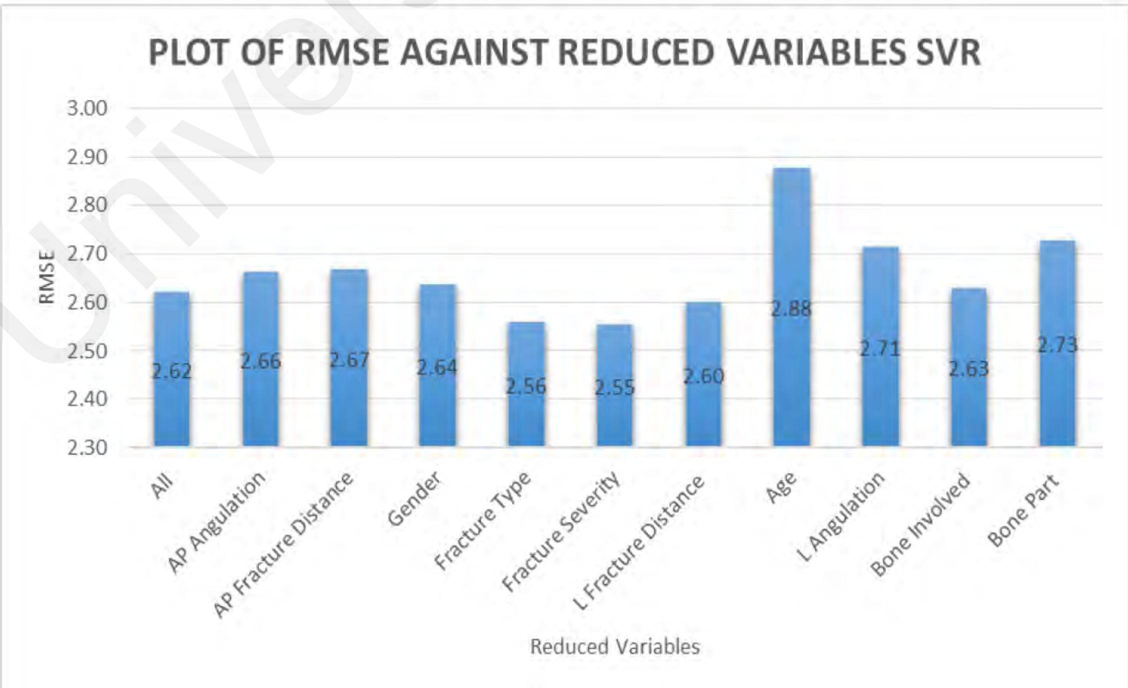


Figure 4.3: Sequential backward elimination on ranked variables based on SVR variable importance method.

Figure 4.4 illustrates a box plot of the RF model using a complete set of variables that resulted in an RMSE value of 2.57 (p = 0.933) and reduced variables with an RMSE value of 2.56 (p = 0.885). The best model for the reduced variables is using ten variables without fracture severity. From the result, we can infer that between expected and actual recovery times, there is no substantial difference.

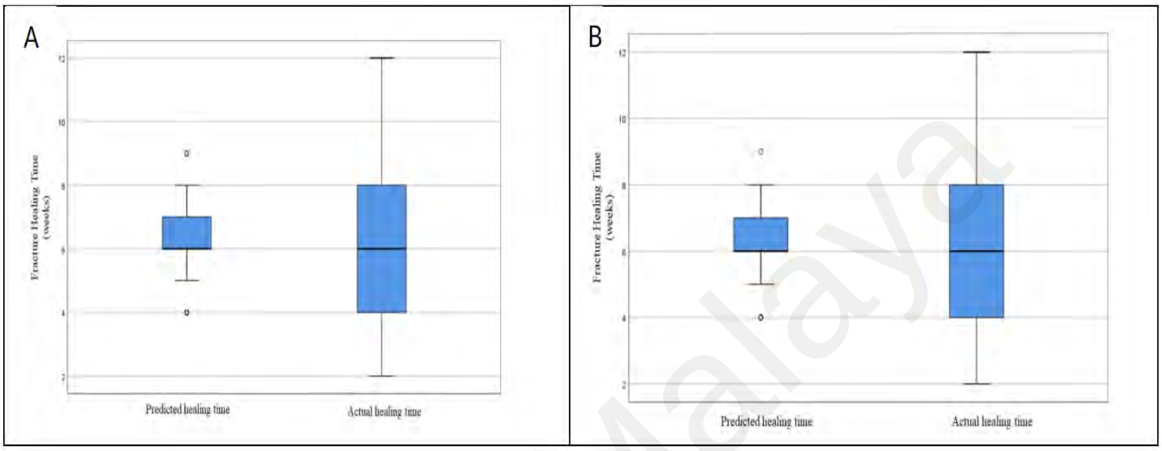


Figure 4.4: Boxplot of the healing weeks value distribution for the RF model with (A) all the variables and (B) the selected variables.

Figure 4.5 illustrates box plot of SVR model using complete set of variables that resulted in RMSE value of 2.62 (p = 0.36) and reduced variables with RMSE value of 2.55 (p = 0.93). The best model for the reduced variables is using bone part, fracture anterior-posterior angulation, distance and age. As there is no apparent variation in healing time between expected and actuality.

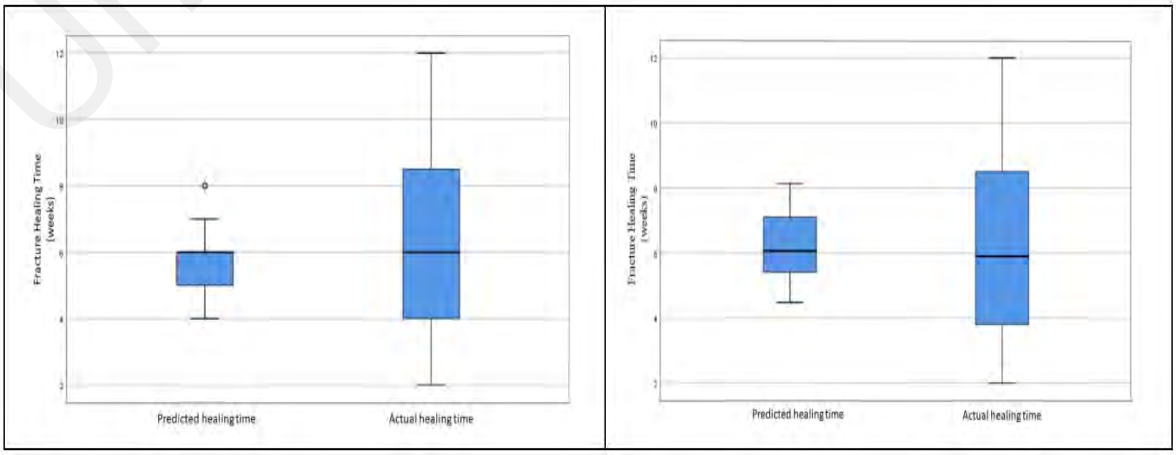


Figure 4.5: Boxplot of the healing week's value distribution for the SVR model with (A) all the variables and (B) the selected variables.

The SOM component plane is shown in figure 4.6, the blue region indicated the low value of the variable, the red region indicates a higher presence of that particular variable. Those average values are situated in the colours between (other colours indicates average value). The blue in the SOM component plane of healing weeks represents fast recovery which is 5 weeks. Paediatric that requires a longer time to recover fully are representaed in the red region and the colours in between indicate the range from 5 weeks to 10 weeks. Age is a significant element that has been discovered as an important variable using the variable selection method. Shorter healing time is noted in younger children age five and below despite higher fracture displacement and angulation. Longer healing time is related to older age, the bone part where fractured occurs and higher fracture angulation or distance. When age is included in the SOM map, the quantitation and topographic error are also higher. The quantization error is reported as 0.160 and the topographic error is reported as 0.021.

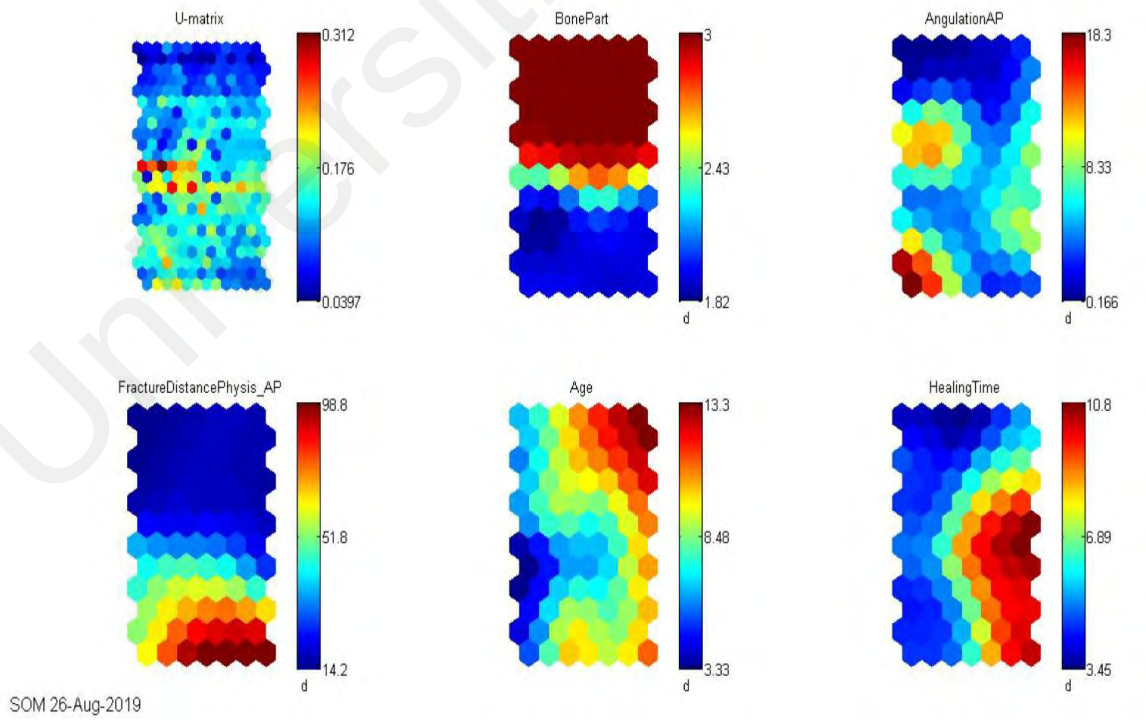


Figure 4.6: SOM U-matrix and component planes of selected variables with healing weeks.

SVR and RF predictive models were developed using both selected variables and all variables from the variable importance method (VIMs) and SBS method. The values of performance metrics for each model are calculated considering all of the eleven input variables and selected variables (i.e.: gender, age, bone involved, bone part and bone segment, fracture type, fracture severity, lateral and anterior fracture distance to physis (measured in millimetre), and lateral and anterior angulation (measured in degree)). RMSE was calculated to evaluate the performance of the models. K-Fold CV is a good method in predicting the model performance by generalizing statistical analysis results to an independent dataset (Geisser S. , 1993).

Models developed using selected variables outperformed models developed using all variables, for RF (RMSE 2.56) and SVR (RMSE 2.55). For the RF model, there is no significant difference from using all variables (RMSE 2.56). As for the SVR model, using all variables outputs an RMSE value of 2.62 which is using selected variables is an improvement (RMSE 2.55). With an RMSE of 2.55, our model predicts test results that are within 2.55 weeks of the real median healing week value for the upper limb data consistent with the research. This period of 2.5 weeks is clinically acceptable in its interpretation. This is due to the fact that patients' follow-up time would be during that interval, about two weeks after the fracture had healed, rather than on the precise day of bone healing. Provided the RMSE value is lower, the better the result produced. SVR model outperforms RF model slightly due to a small difference with models using all and reduced variables. Previous studies conducted which developed ANN, SVM and RF model in predicting the risk of osteoporosis concluded that the SVM model outperformed other machine learning methods with higher accuracy (Geisser & Johnson, 1993) (Kim, Yoo, & Kim, 2013). SVM refines accuracy through optimization in a higher-dimensional space with the use of a kernel. Therefore, it generates better result in comparison to the RF model in this study. SVR is applied in this research seeing as it's a non-parametric approach that does not rely on the underlying dependent and independent variable distributions. It is controlled by the kernel function. SVR outperformed slightly than RF, due to SVR followed the trends in the healing time (weeks) between the actual and predicted values. It is maybe because SVR for regression are known to be good at pattern recognition and functions fitting.

To determine the list of variable importance (VIMs), both RF and SVR models were adapted. It is essential to generate VIMs as it is an crucial part of contributing to good model performance. As SBS algorithm depends only on importance as an adequate term to eliminate unimportant variables one by one from a model (Royston & Sauerbrei, 2008) (Vittinghoff, Glidden, Shiboski, & McCulloch, 2011). The variable is marked as important when it causes the RMSE value to increase when it is eliminated. This condition is stated with regard to the 'purposeful selection algorithm' concept. The said concept merges the importance and change of RMSE values in the testing set in selecting significant variables (Bursac, Gauss, Williams, & Hosmer, 2008) (Dunkler, Plischke, Leffondré, & Heinze, 2014). Backward elimination technique is used to obtained important variables in this study, those important variables are bone part, age, fracture angulation, fracture distance. The selected variables conform to statistical significance with $p < 0.005$ except for age.

The SOM technique presented in this study, allow us to visualized in a 2-dimensional representation. If there is confidence in the original training data, this allows the clinician to place a new patient within the context of previous or similar cases. In comparison to other factors, we discovered that age was the most important determinant of recovery time as compared to other variables. The younger children healed faster, despite the fracture being further away from the physis and did not vary with the bone part. Younger children have a thicker, osteogenic periosteal layer of bone.

This enables the healing process to be initiated quicker and also helps with the eventual remodelling and strengthening of the bone once united.

In older children, age seven and above, the following variables were found to influence the healing time. The closer the fracture was to the physis, the faster the healing time. This is consistent with the known physiology of the bone. The physis is the centre that makes new bone and enables longitudinal bone growth. The area closer to the physis are highly osteogenic and as contributes to the healing of fractures.

Fractures with less angulation also healed faster. This is because, with less angulation, there is less displacement of the fracture from the normal anatomy. As such, the process of healing occurs more rapidly as there is more contact area between the fracture fragments, which promotes the formation of bone callus. Hence, bone angulation can be concluded as one of the parameters affecting the healing time in children.

Fractures involving the distal part of the bone healed faster. This is in comparison to diaphyseal fractures. The circulation and abundance of osteogenic factors in the metaphyseal region of the bone, enable more rapid healing for fractures in this bone part (Staheli L. T., 2008) (Schwartz, Rozumalski, Truong, & Novacheck, 2013). However, the rotation of long bone fractures used in this study is difficult to quantify using just radiographs and x-rays. For accurate rotation, CT scans would be required. As such, rotation was deemed not a criteria and rotation alone does not change the healing time rate or predictability of healing time in fractures.

From the results, we can infer that RF and SVR models developed have proven their capabilities as a tool in estimating and selecting significant variables that will affect fracture healing rate. Beside, this expert system can be used to detect children with a potentiality of having extra healing time which may need extra attention. It is not feasible to claim that the findings presented have universal application at this time. If used within a validation system and more models created to compare the prediction ability, it can create a functioning application where contributions will be made to clinicians to keep in the tab of patients' progress or evaluate any particular risk.

4.2 Kids Fracture Expert System Patient Management Aftercare Guide

This study is developed system prototype focusing on orthopedic pediatric, including various functions; fracture identification, bone fracture healing rate and fracture management aftercare. The system prototype uses decision support system concept for fracture identification. The fracture healing time prediction is deployed using machine learning algorithm as discussed in section 4.1. The system also integrates patient management guide after identification of the fracture type among children patients, expert suggestion regarding aftercare of the fracture is also incorporated and display to the user.

Expert knowledge were collected and applied into our system using the decision support system concept. The illustration below shows in figure 4.7, figure 4.8, figure 4.9, figure 4.10, figure 4.11, figure 4.12 and figure 4.13 can be found in the system for ease of user in identifying the fracture type among children.

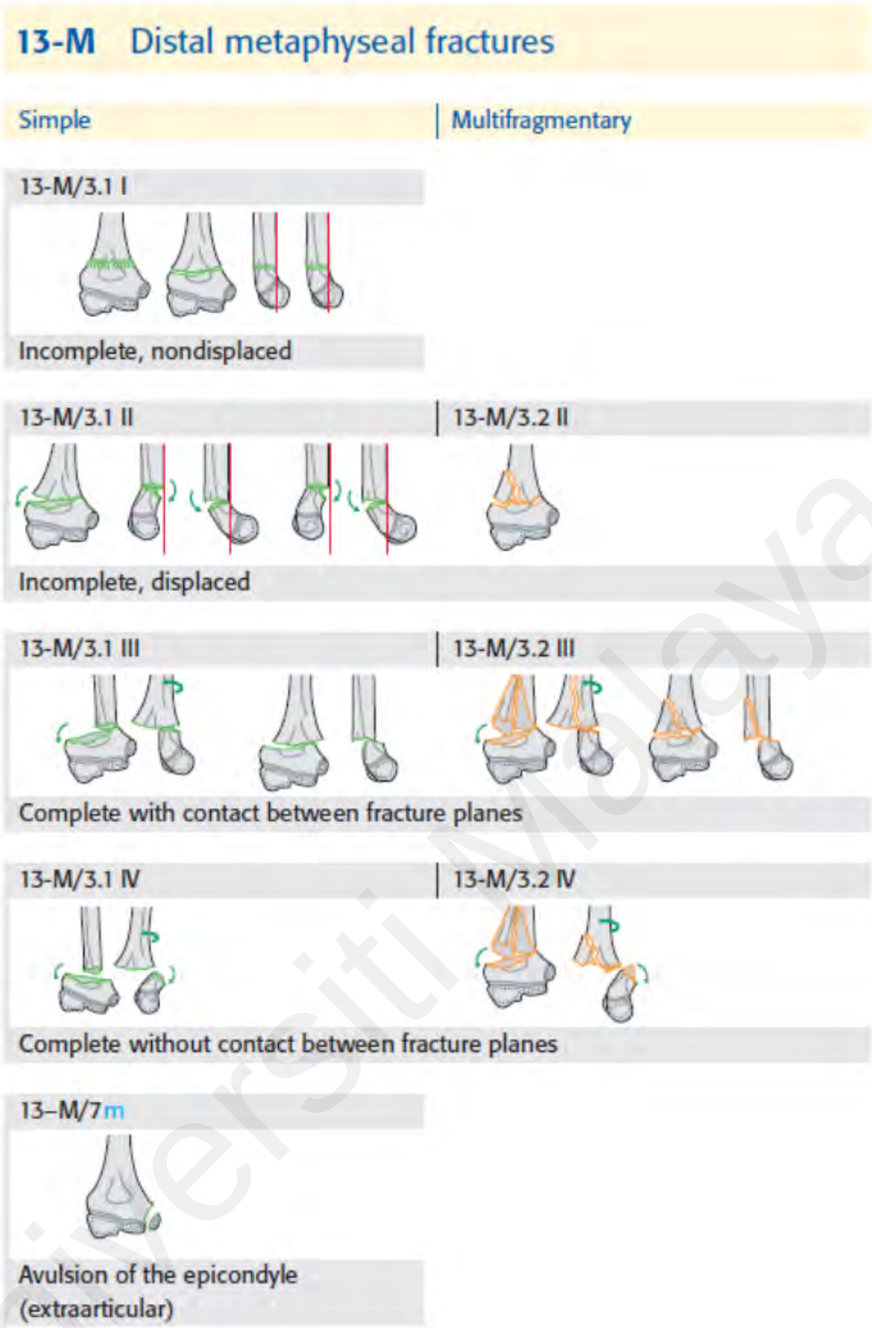


Figure 4.7: Supracondylar Humerus Fracture 13-M

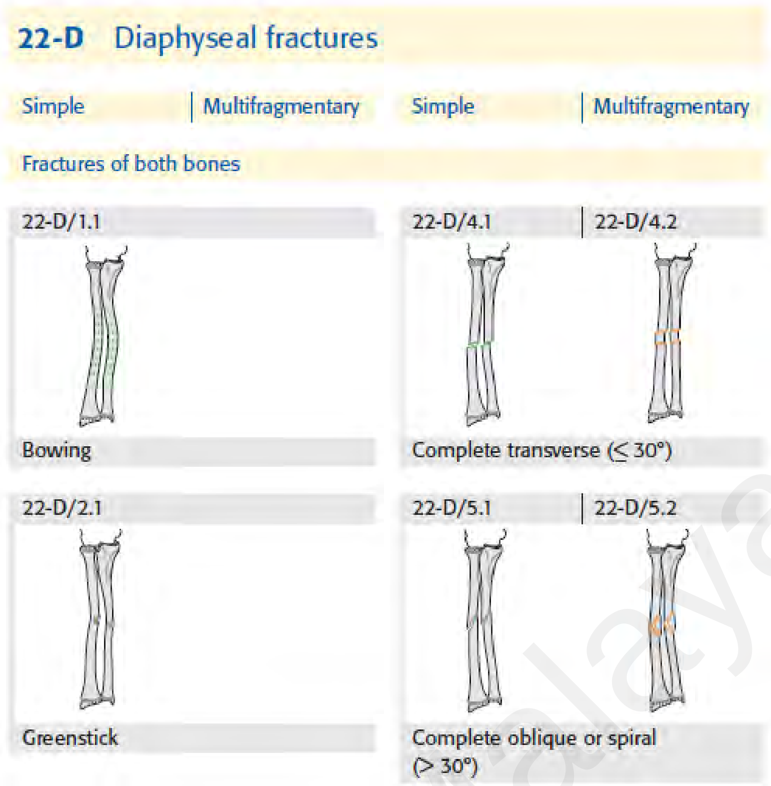


Figure 4.8: Radius & Ulna Diaphyseal Fracture 22-D (Both Radius and Ulna)

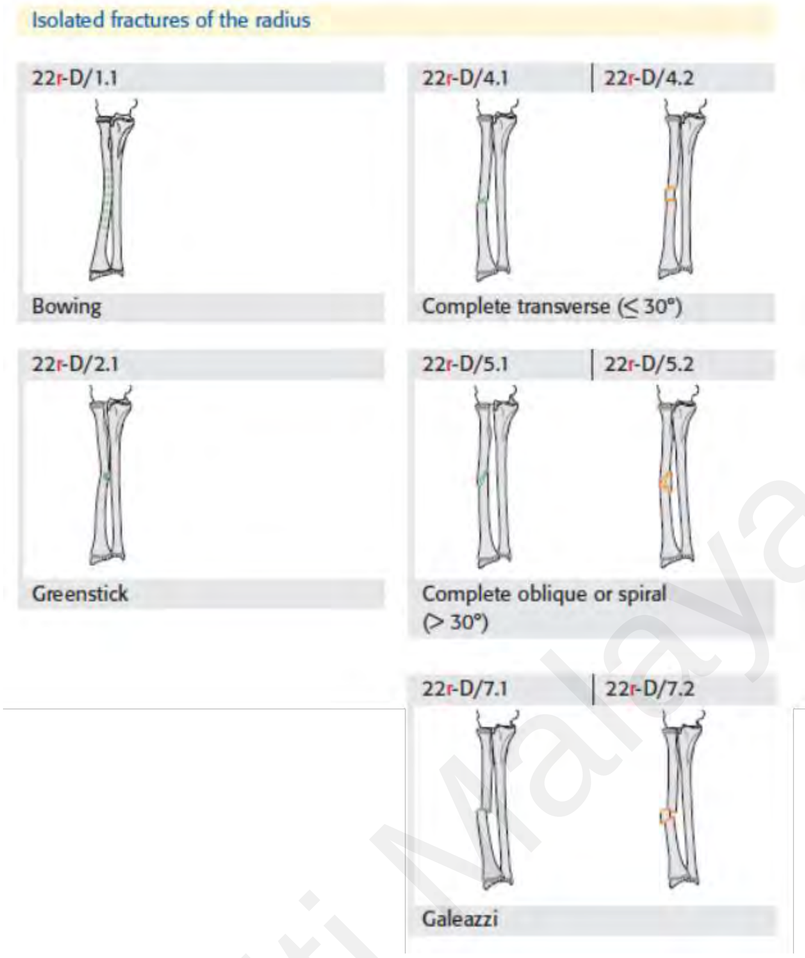


Figure 4.9: Radius & Ulna Diaphyseal Fracture 22-D (Isolated fractures of the Radius)

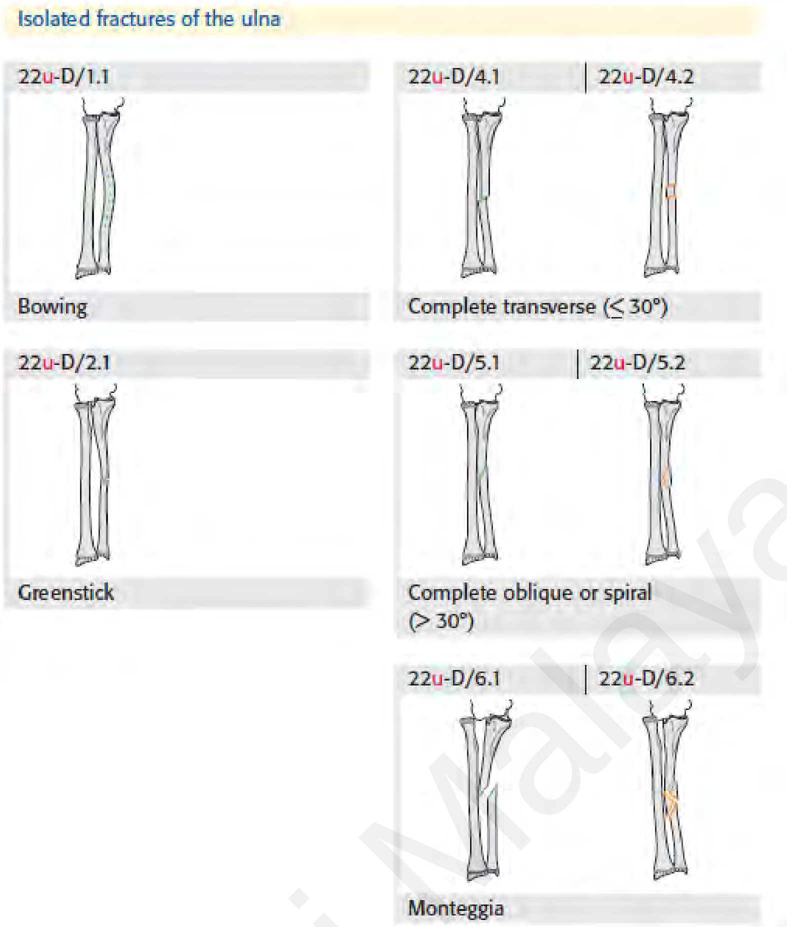


Figure 4.10: Radius & Ulna Diaphyseal Fracture 22-D (Isolated Fractures of the Ulna)

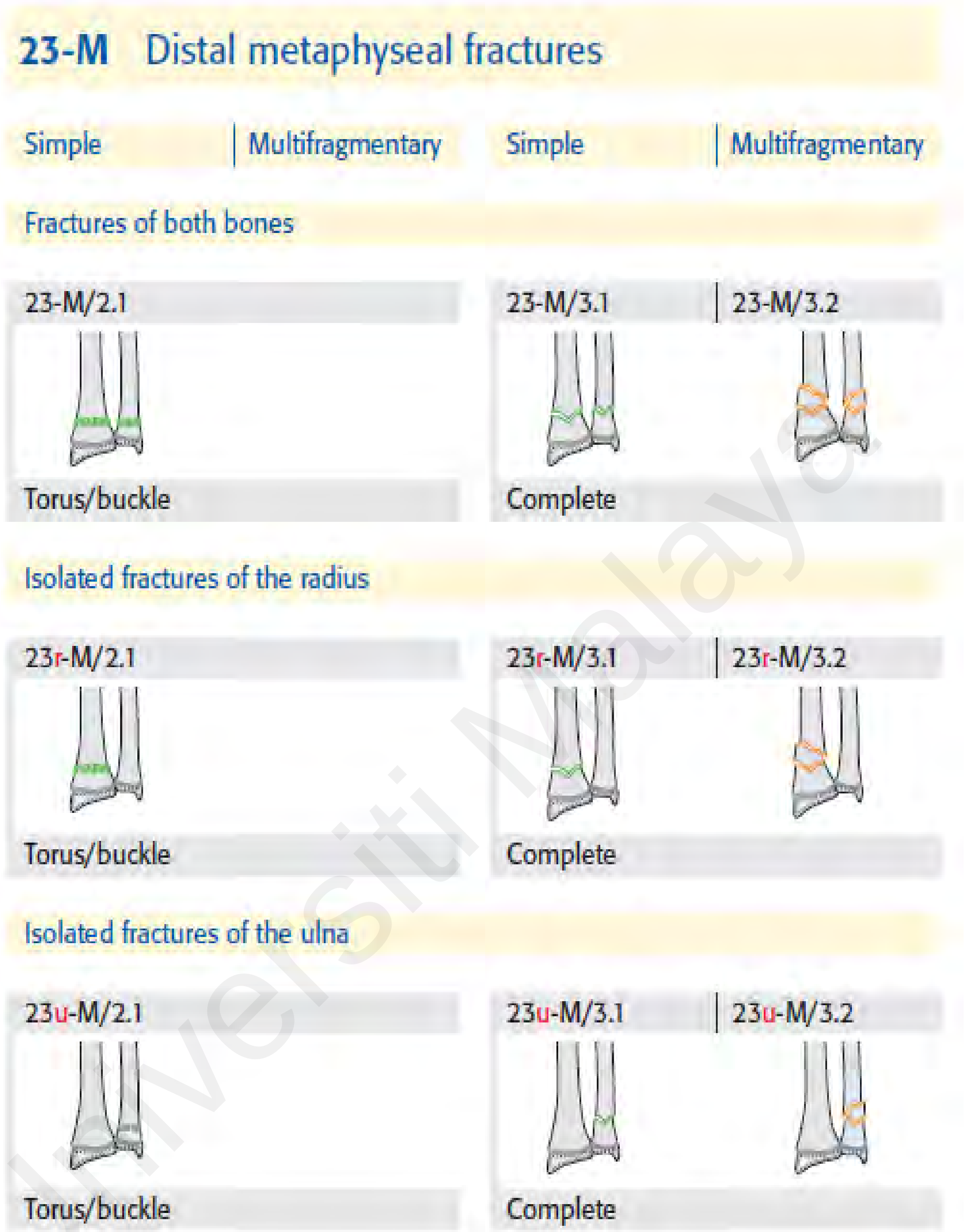


Figure 4.11: Distal Radius & Ulna Fracture 23-M of both bones, Isolated Radius Fracture and Isolated Ulna Fracture.

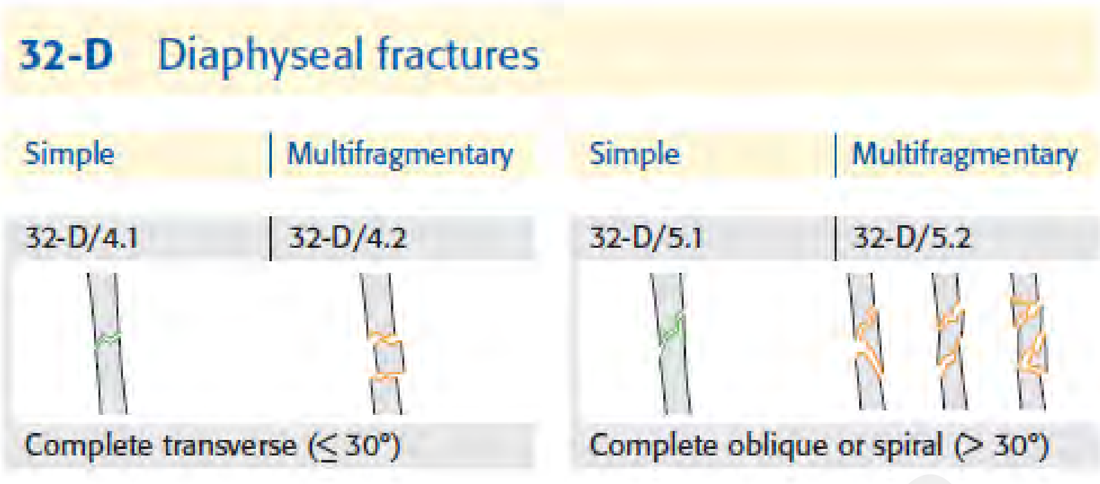


Figure 4.12: Femur Diaphyseal Fracture 32-D

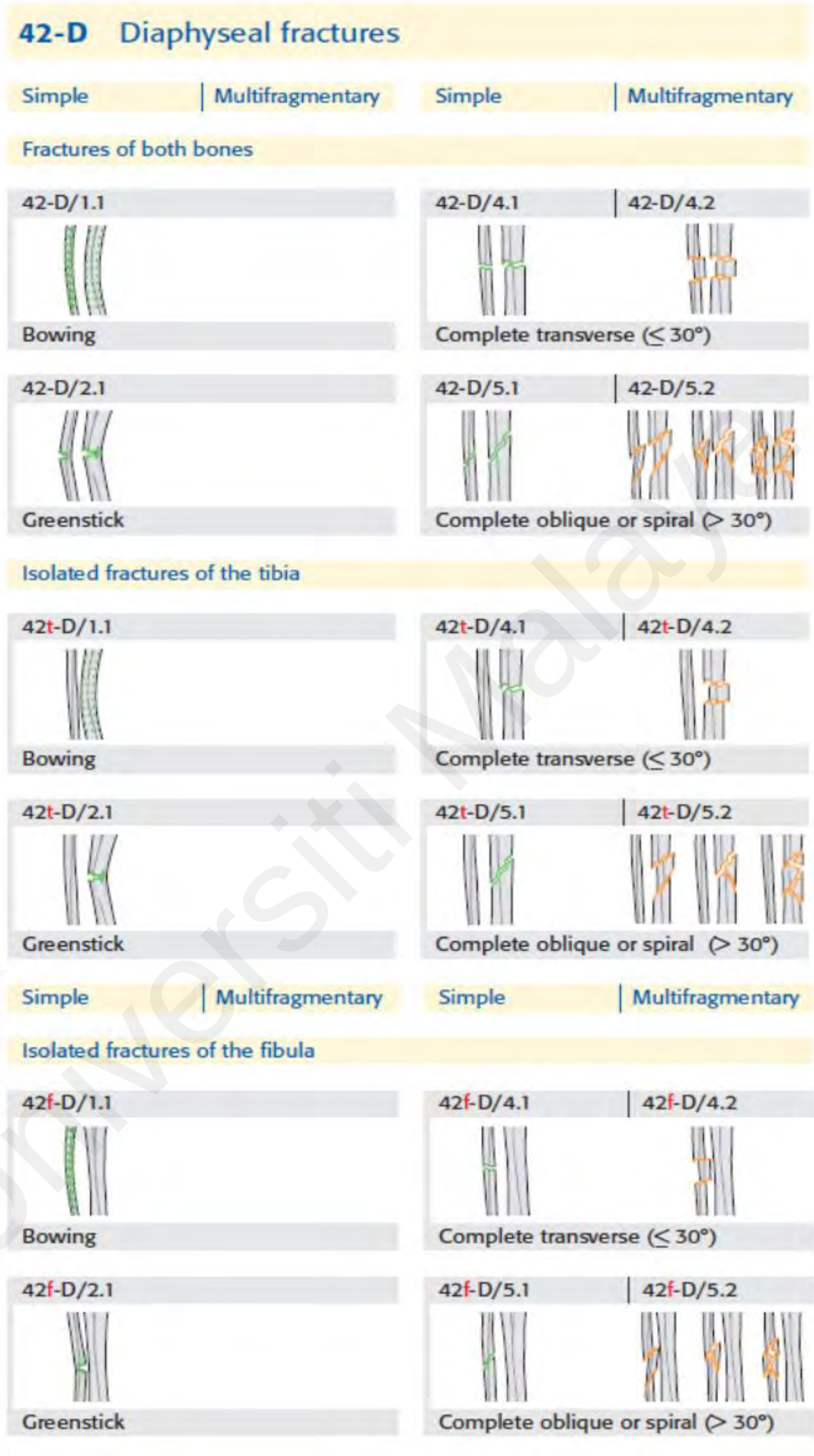


Figure 4.13: Tibia & Fibula Diaphyseal Fracture 42-D include both bones, isolated fractures of Tibia and Isolated fractures of the Fibula.

The graphics of pediatric trauma aftercare algorithm with expert suggestions is shown in Figures below (4.14, 4.15, 4.16, 4.17, 4.18, 4.19, 4.20, 4.21, 4.22, 4.23 and 4.24), where user enters on types of fracture and the fracture details, the system will suggest the aftercare guide, including backslab, applying POP cast or refer to orthopedic specialist. Backslab is the simplest form of plaster splint, which is to provide support with less risk of limb constriction.

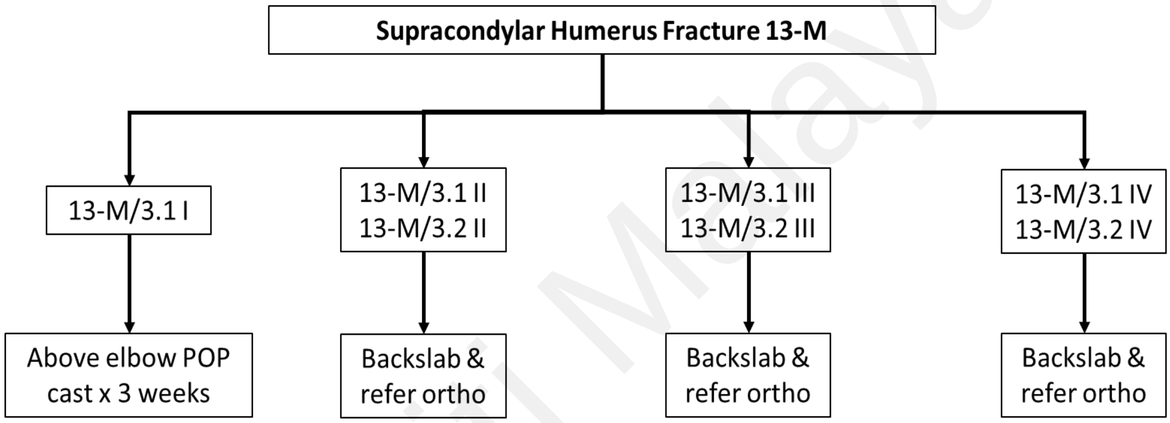


Figure 4.14: Suprecondylar Humerus Fracture 13-M with expert suggestions.

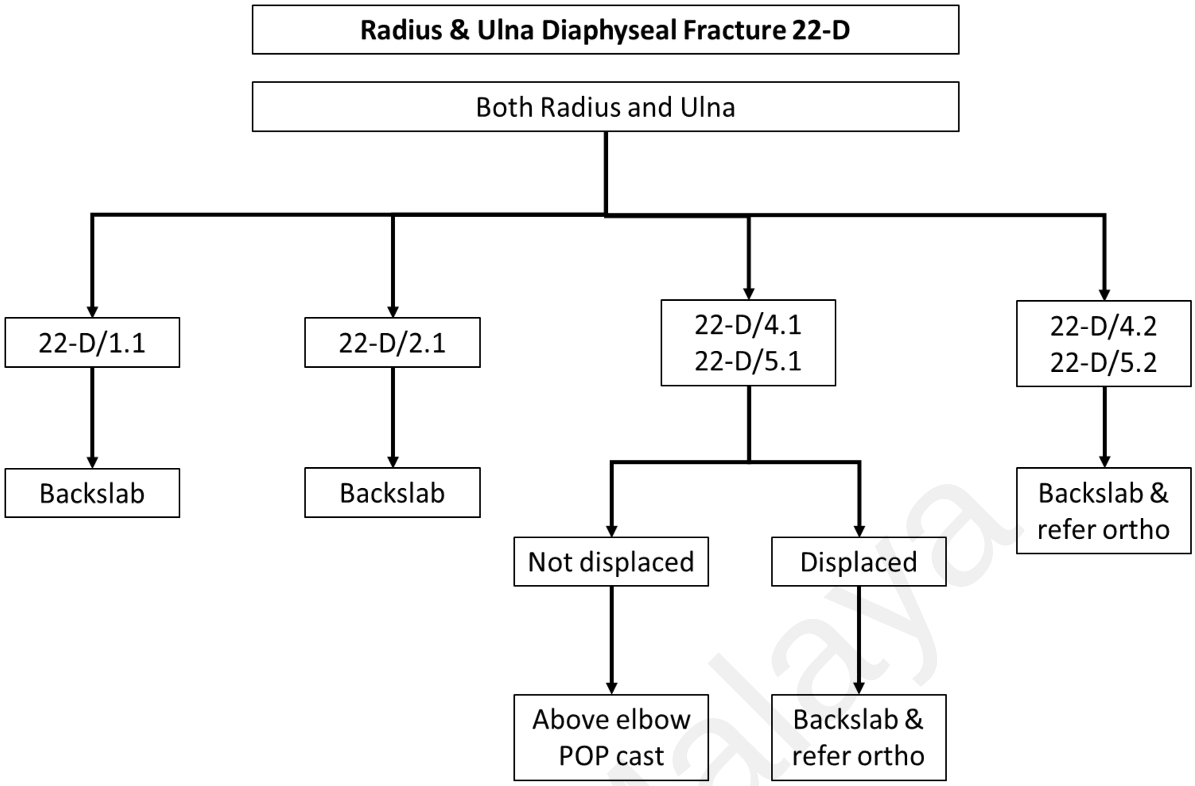


Figure 4.15: Radius and Ulna Diaphyseal Fracture 22-D, multifragmentary fracture involving both Radius and Ulna with expert suggestions.

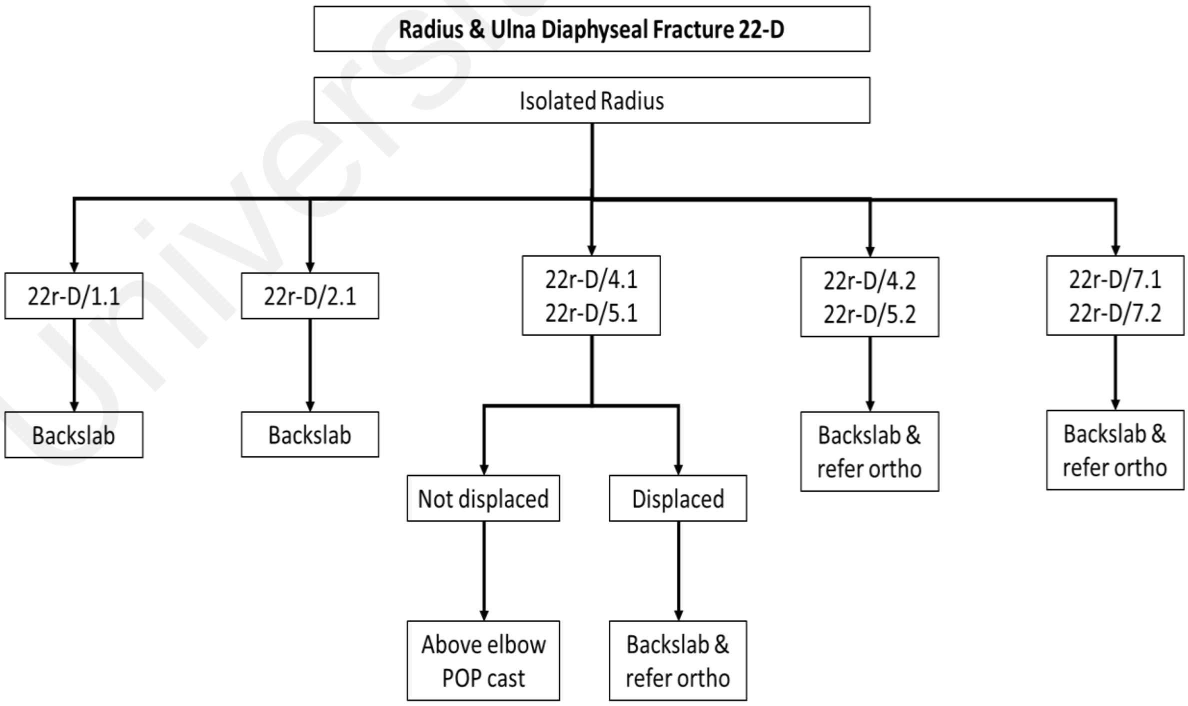


Figure 4.16: Radius and Ulna Diaphyseal Fracture 22-D involve isolated radius fracture with expert suggestions.

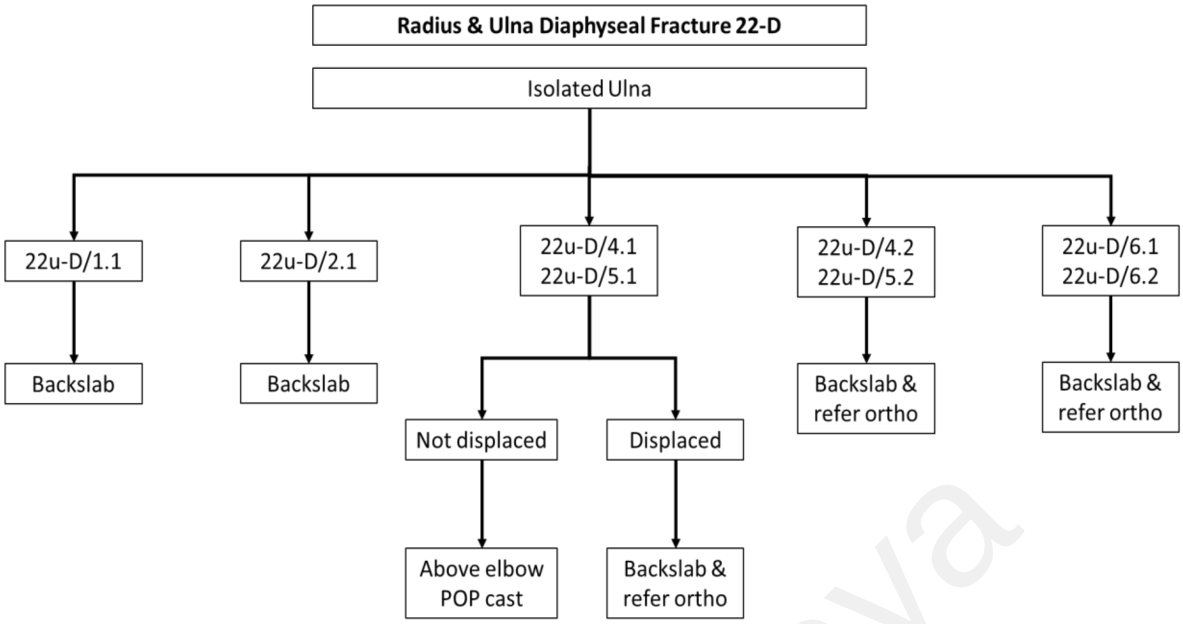


Figure 4.17: Radius and Ulna Diaphyseal Fracture 22-D involve isolated ulna fracture with expert suggestions.

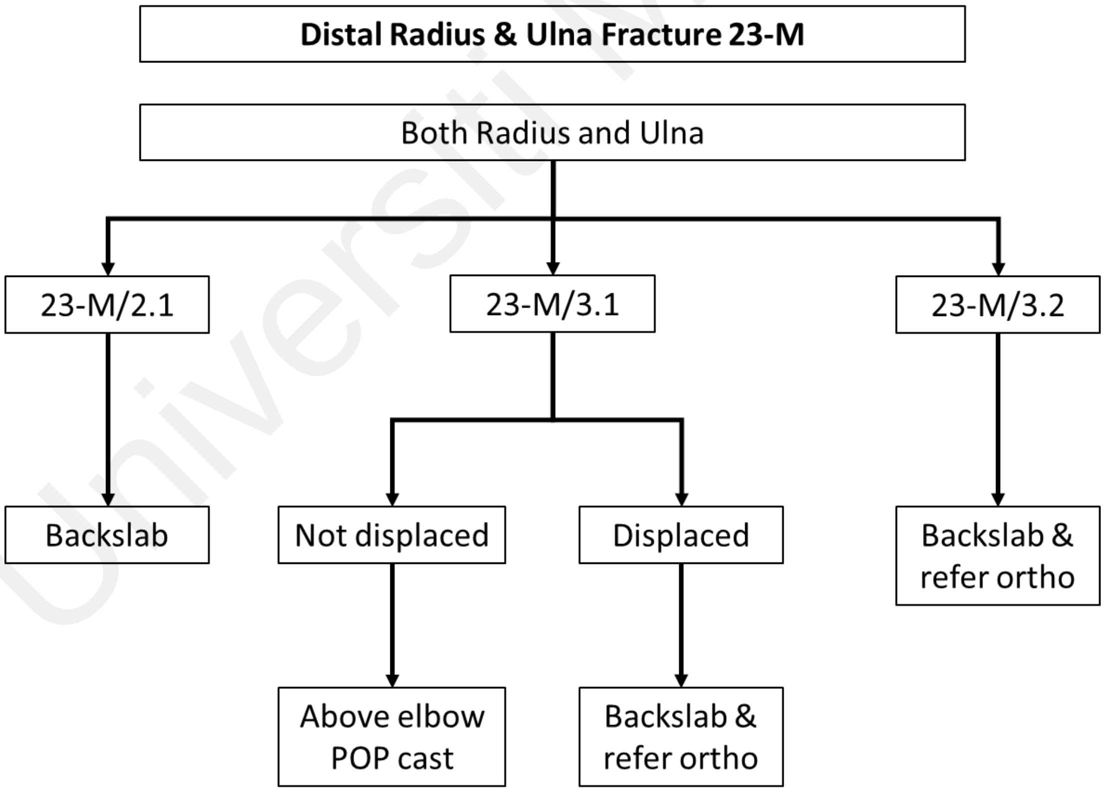


Figure 4.18: Distal Radius and Ulna Fracture 23-M involve both radius and ulna with expert suggestions.

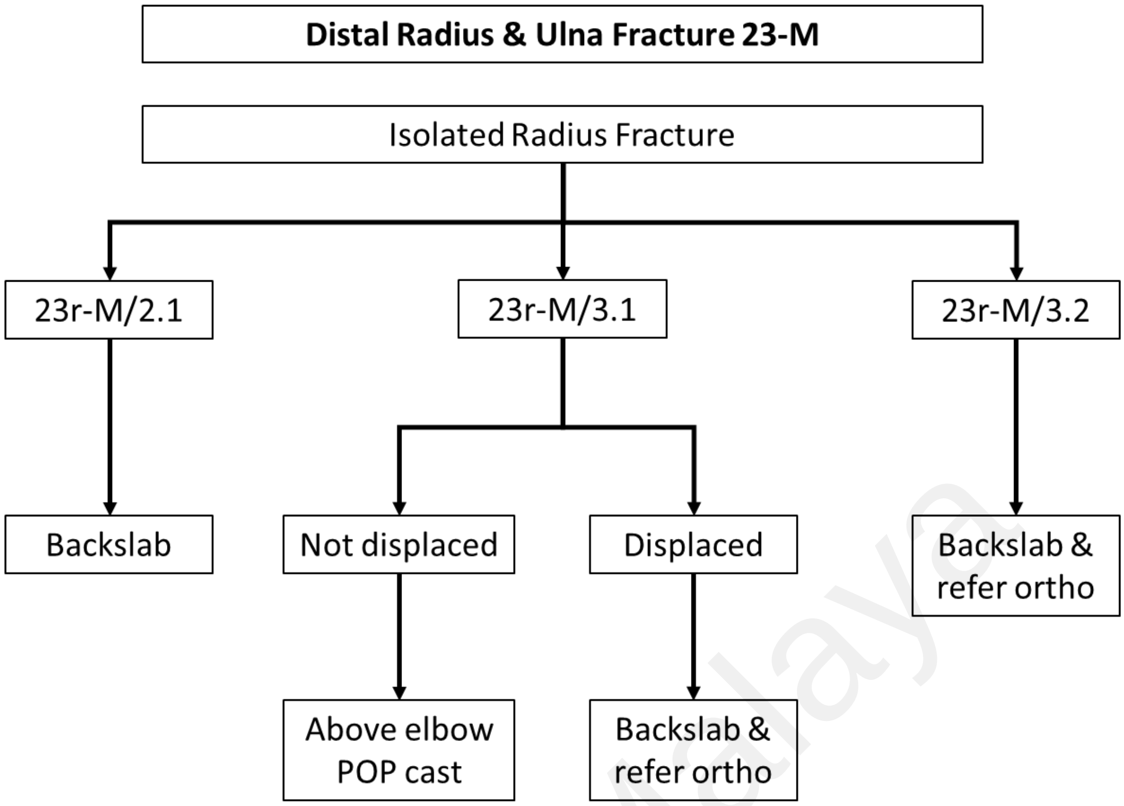


Figure 4.19: Distal Radius and Ulna Fracture 23-M involce isolated radius fracture with expert suggestions.

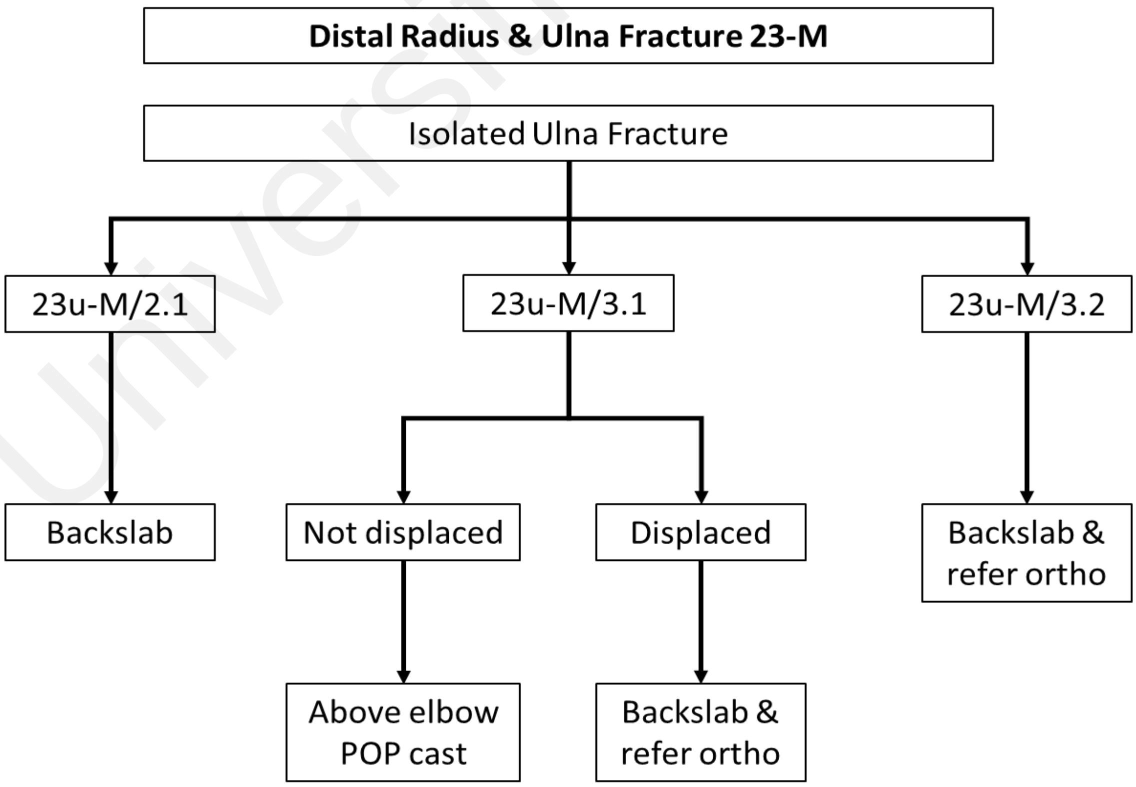


Figure 4.20: Distal Radius and Ulna Fracture 23-M involve isolated ulna fracture with expert suggestions.

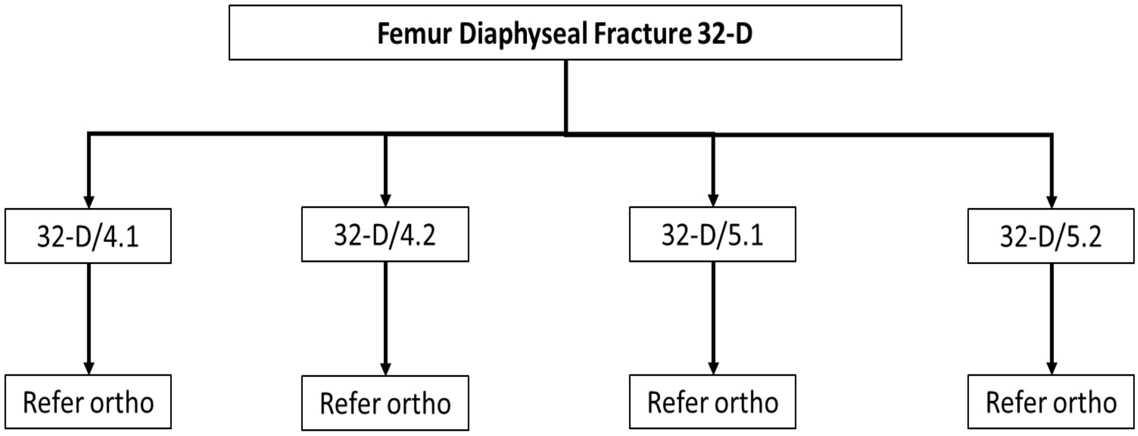


Figure 4.21: Femur DIaphyseal Fracture 32-D with expert suggestion, basically with this type of fracture, experts suggest referring to orthopaedic specialist.

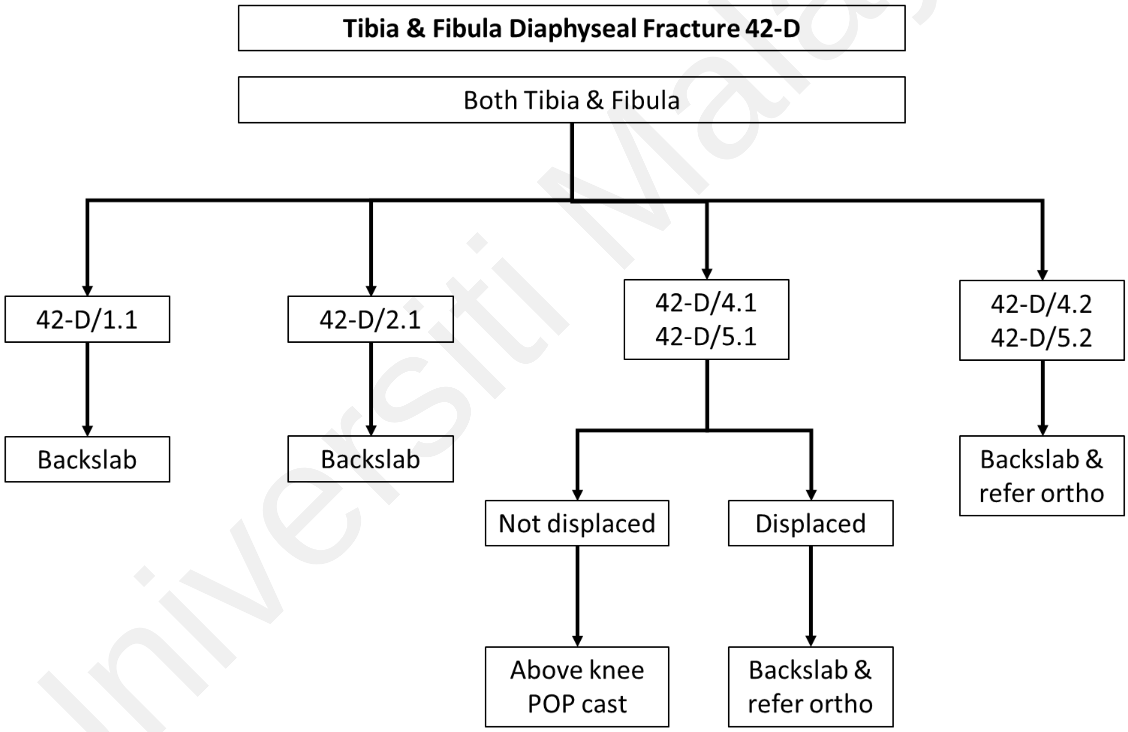


Figure 4.22: Tibia and Fibula Diaphyseal Fracture 42-D involving both Tibia and Fibula with expert suggestions, include applying backslab, above knee POP cast and referring to orthopaedic specialist.

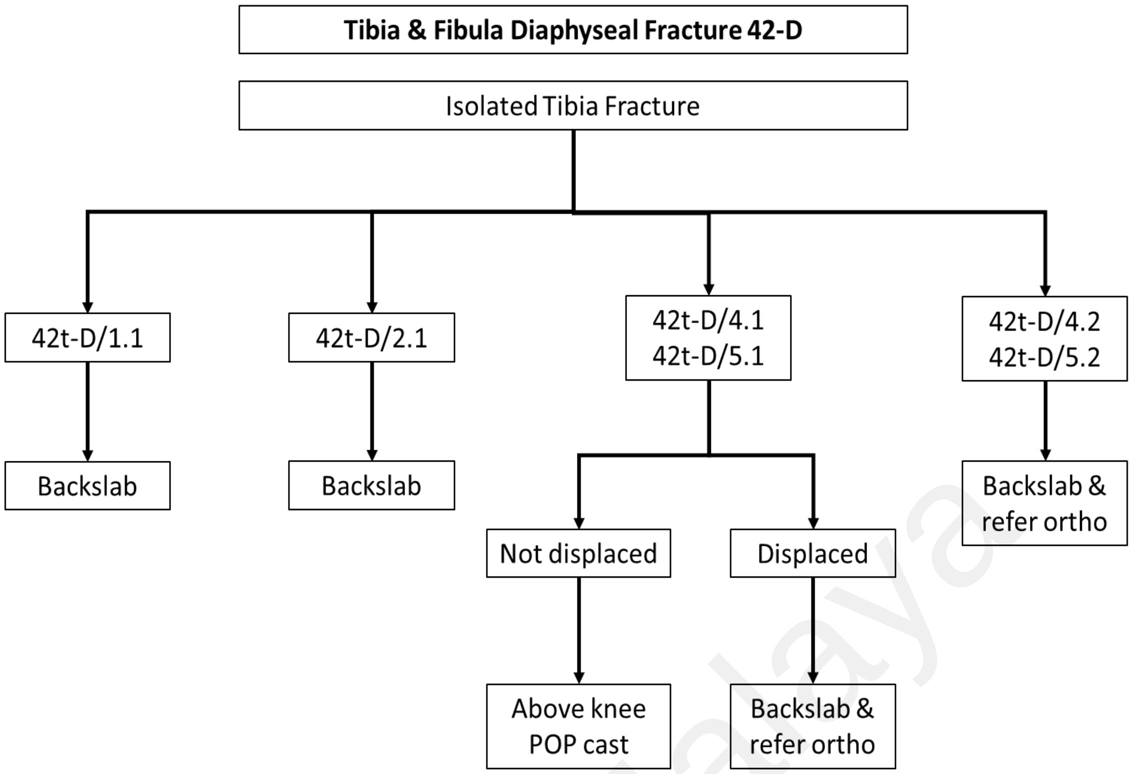


Figure 4.23: Tibia and Fibula Diaphyseal Fracture 42-D involve isolated Tibia Fracture with expert suggested solution.

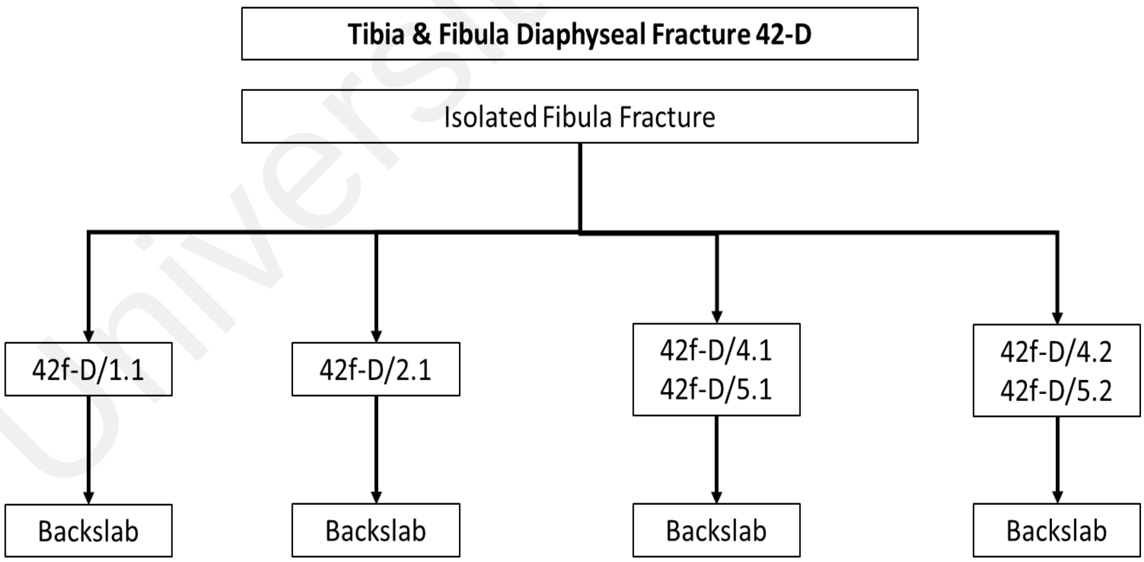


Figure 4.24: Tibia and Fibula Diaphyseal Fracture 42-D involving Isolated Fibula Fracture. For this type of injury, expert suggested to apply backslab to treat the fracture.

4.3 Orthopaedic Expert System (Kids Fracture Expert)

Kids Fracture Expert is an online system that able to predict the fracture healing time for paediatric patients. The machine learning model as described in Part A and Part B is integrated into the online expert system. It is mainly provided for medical practitioners especially orthopedists to aid and provide insights for them regarding the expected healing time of the patient. The outcome of the expert system is shown and discussed in this section, including the user interface is also included and described in detail.

Website: http://kidsfractureexpert.com/

4.2.1 Homepage of Kids Fracture System

Figure 4.25 and Figure 4.26 shows the homepage when the users enter the website http://kidsfractureexpert.com/ on the web browser. The homepage shows a demo of the expert system that allows user to test on the system, by entering the required information, at the bottom of the page will display the predicted healing time according to the user input information.

The 'Login' and 'Register' is located on the top of the page. For existing user will then login to their respective account. As for new users, they are required to register a new account and the system admin will have to approve the registered user.

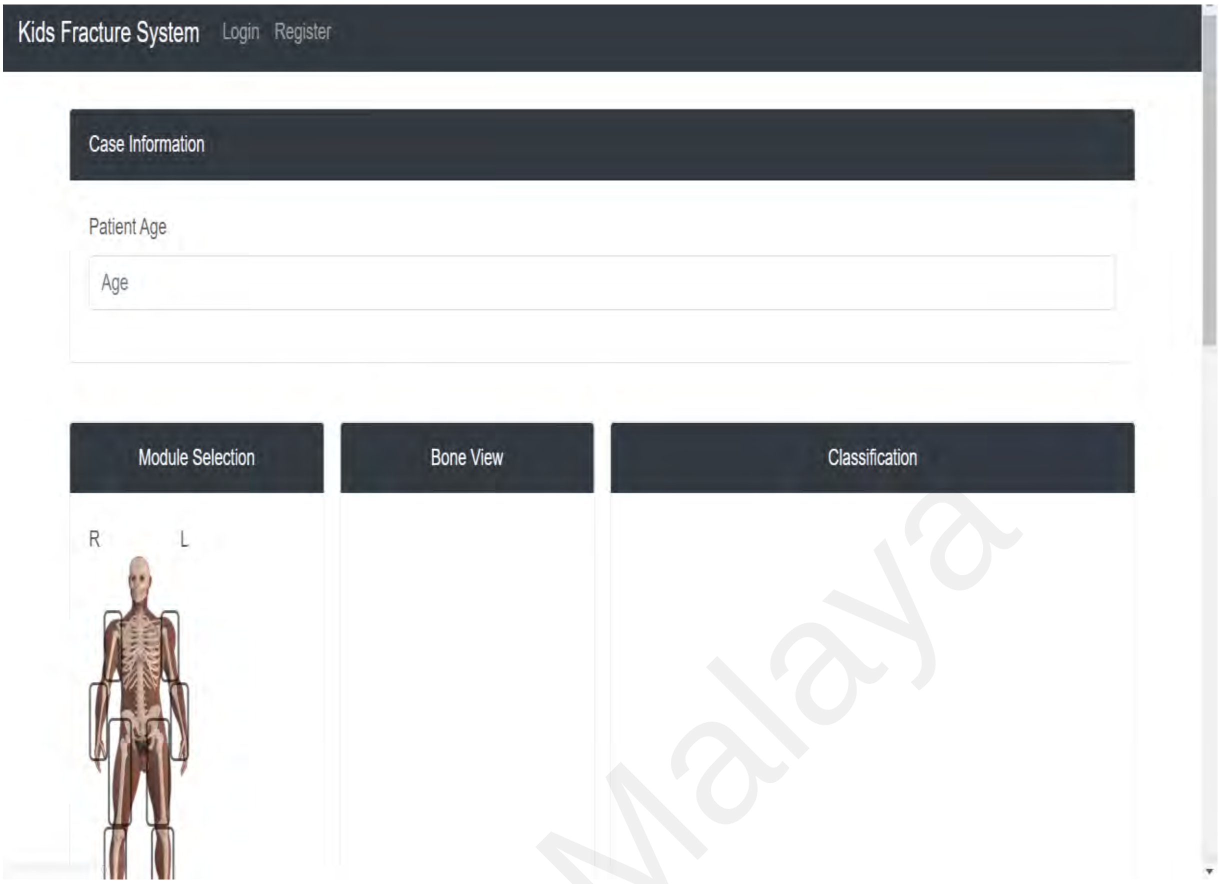


Figure 4.25: Homepage of Kids Fracture System

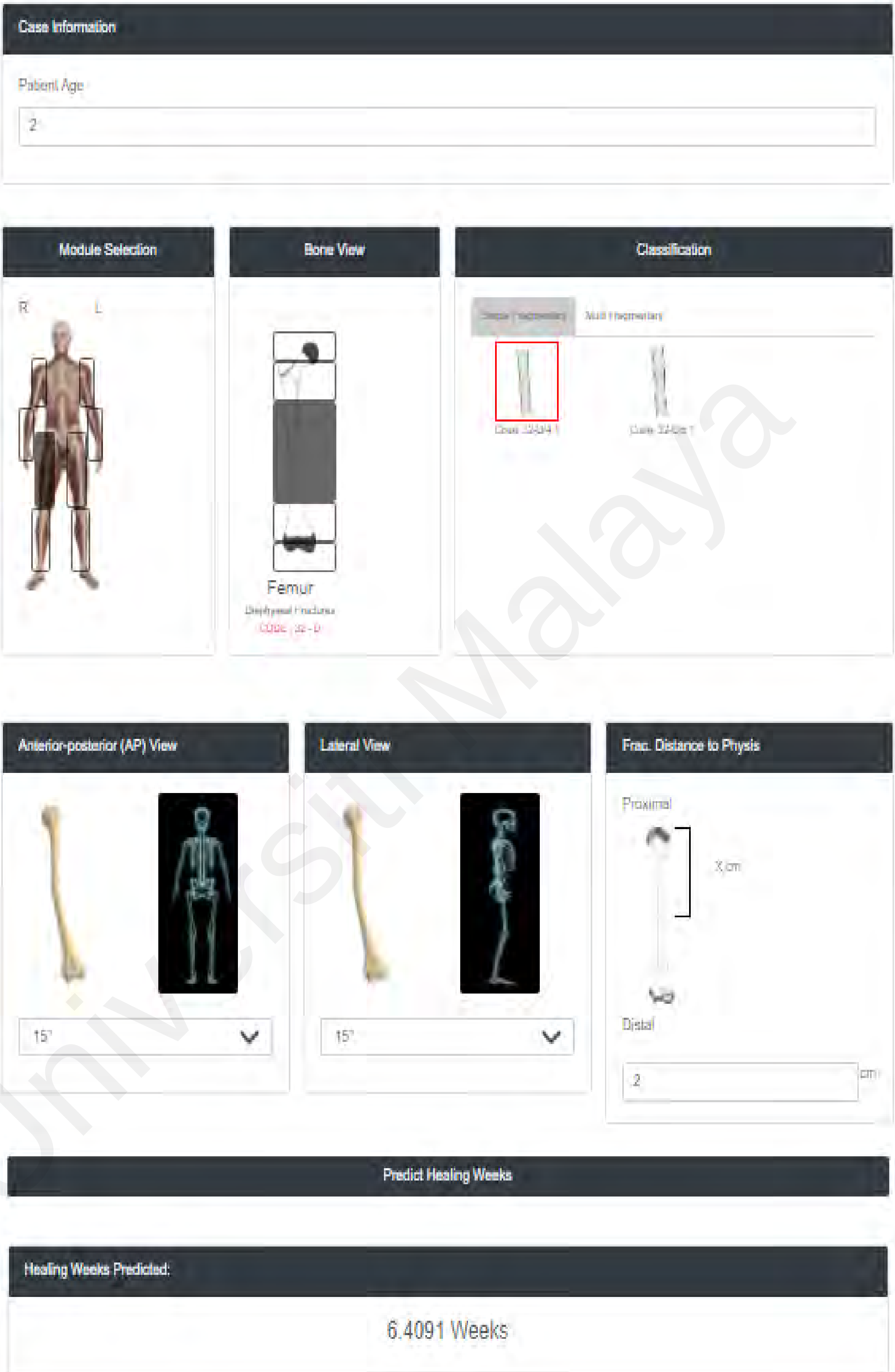


Figure 4.26: Extension of Kids Fracture Expert Homepage that allows guest to input data and predict the healing weeks.

4.2.2 Kids Fracture Expert Login Page

Existing user will have to login to their own account, if the user forgot their password, the user will have to click on 'Forgot Your Password' and an email will be sent to reset their account as shown in Figure 4.27. For new user, they are required to register a new account by providing their email and set up their own password as shown in Figure 4.28.

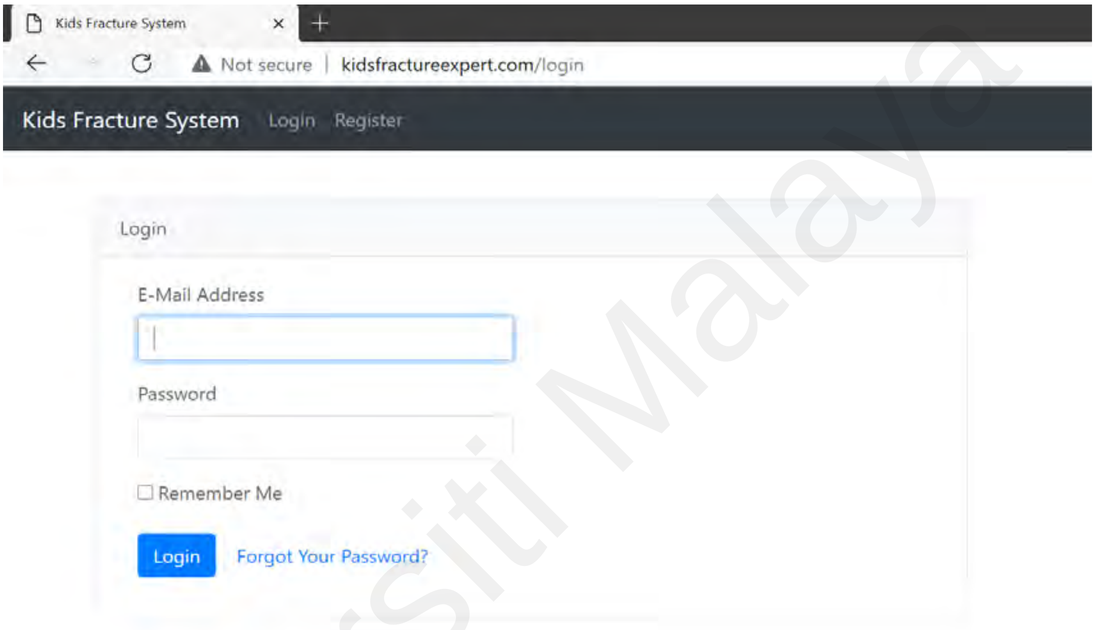


Figure 4.27: Kids Fracture System User Login Page

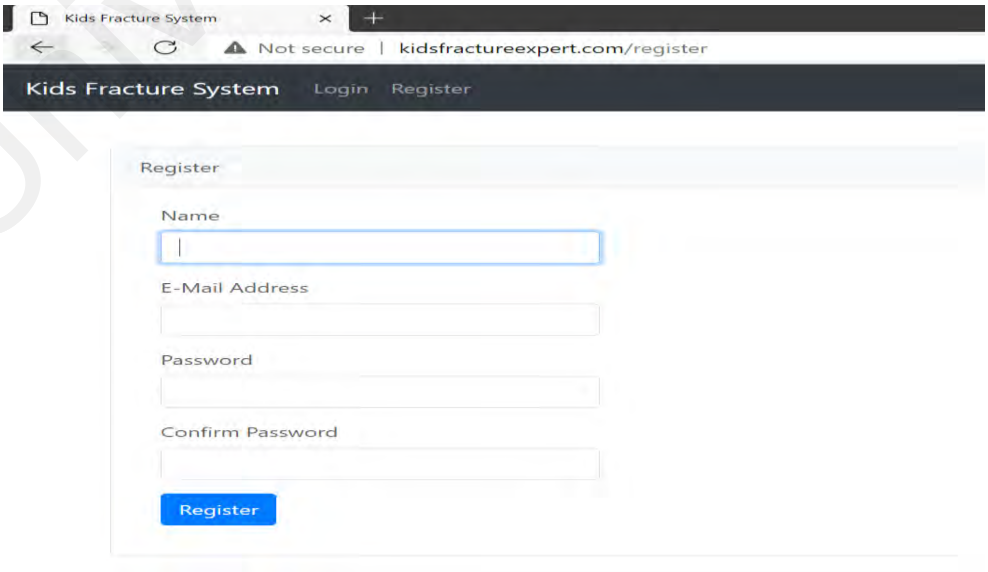


Figure 4.28: Kids Fracture Expert New User Registration Page.

4.2.3 Kids Fracture System Dashboard

Figure 4.29 is displayed once the user successfully login to the system. The dashboard displays the patient name and the user can 'Add Case', as the patient might have more than one fracture. 'View', that allows the user to view the input data that has stored in the database. 'Edit' allows the user to edit that patient data and 'Delete' button can delete the patient information.

As for the new patient, the user will need to register the patient and input the required information, thus the system can predict the healing time.

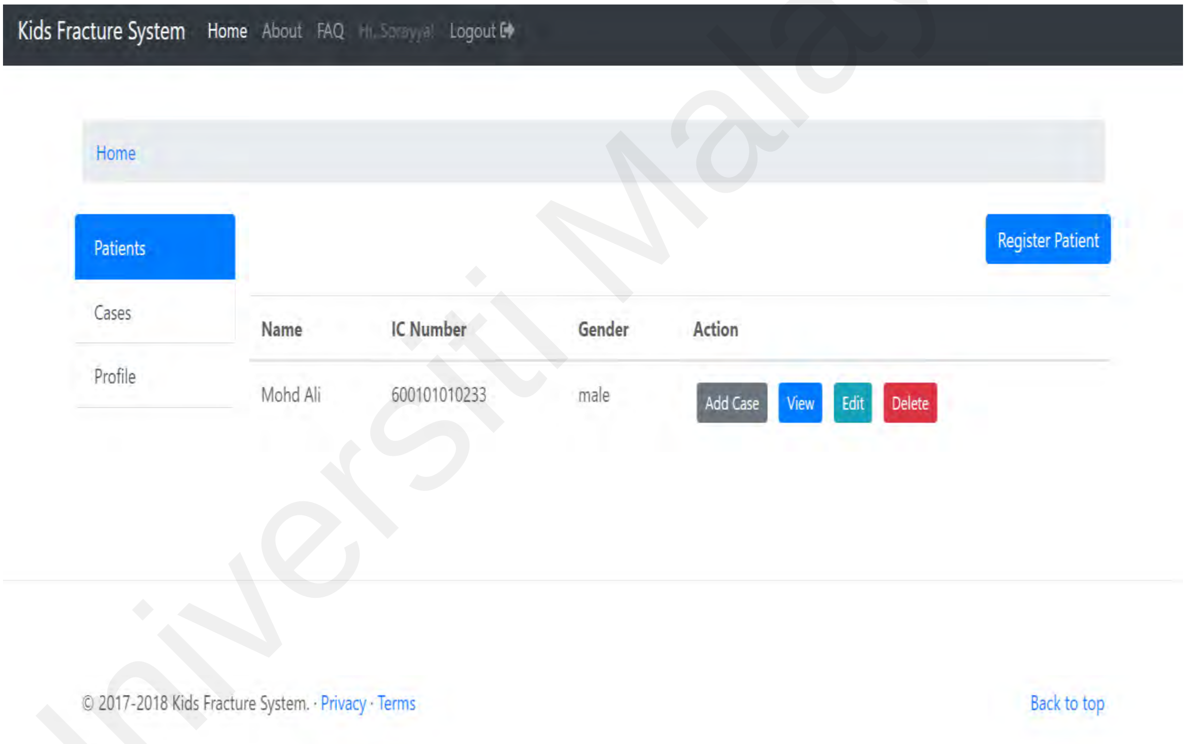


Figure 4.29: Kids Fratucre System Homepage Once User Successfully Login (Dashboard).

4.2.4 Kids Fracture System Edit Patient Page

Figure 4.30 show the pages that allow user to edit patient information. The 'Case Information' requires the user to enter information such as date entry, date injury, time injury, hospital name, place incident, road incident, previous fracture, previous fracture description, medical history, the surface of impact, mechanism of injury, witness, witness description. Then, under the 'Bone Involved' section, there is an interactive skeleton the user able to select the bone part that is injured, followed by the segment of bone, fracture morphology, Anterior-posterior (AP) view, lateral view, and fracture distance to physis. Once the information is done updating, the user has to click on the 'Update' button and the updated data will be stored in the database.

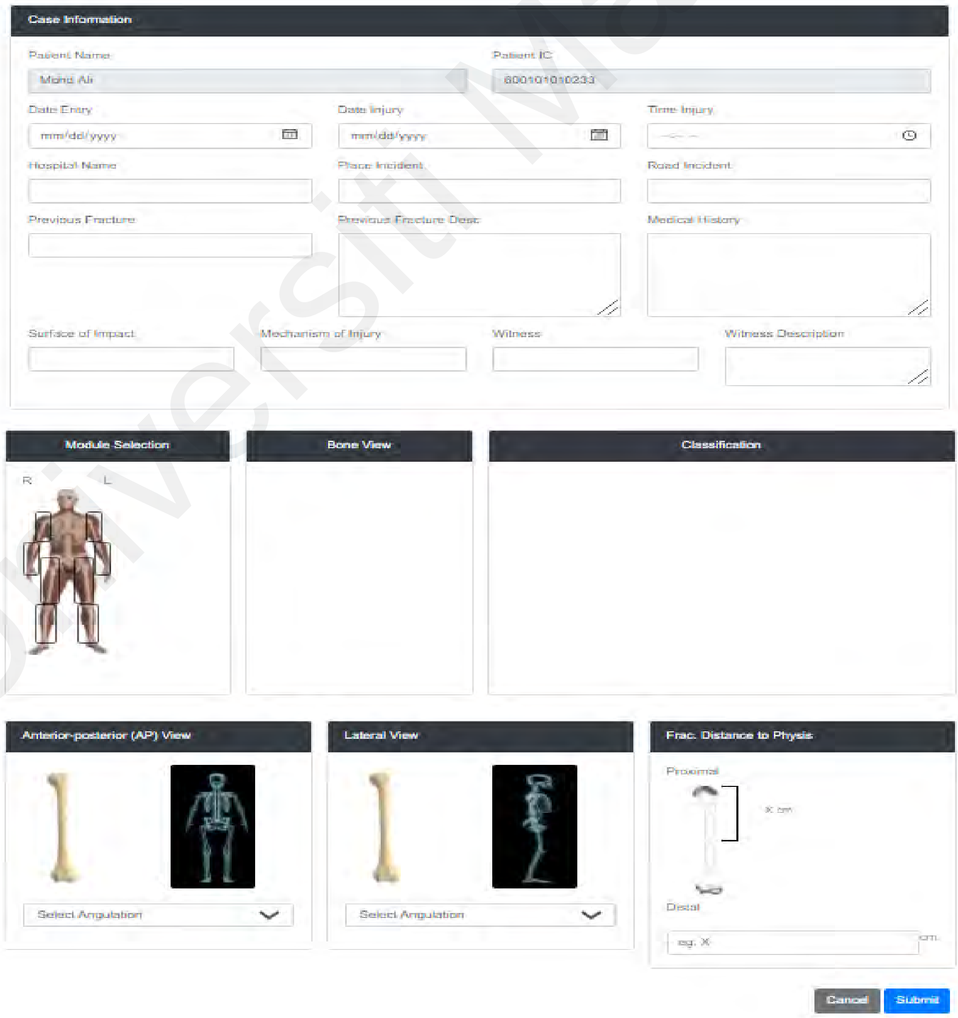


Figure 4.30: Kids Fracture Expert Patient Fracture Case Information Page.

Figure 4.31 shows the basic patient information page, including name, IC number, gender, age, residence type, and parents' information which are the education and occupation of the parents. Once the 'Submit' button is clicked, the information is automatically updated in the database and the updated data is displayed on the dashboard as shown in Figure 4.32.

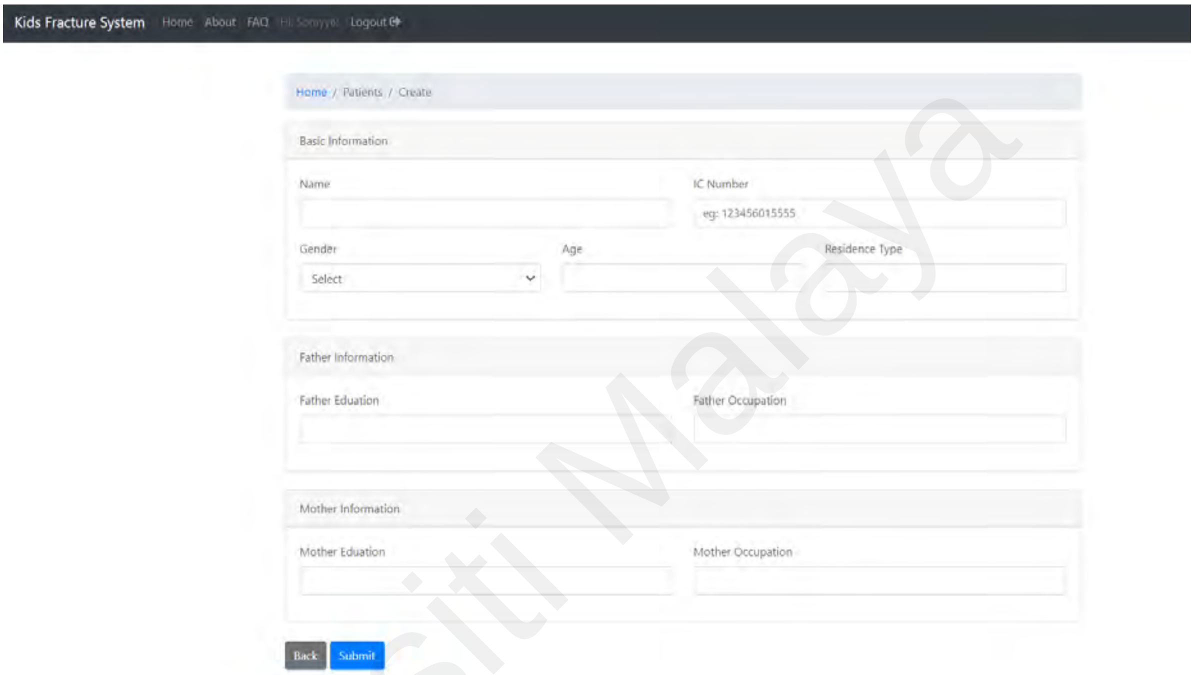


Figure 4.31: Patient Basic Information Page.

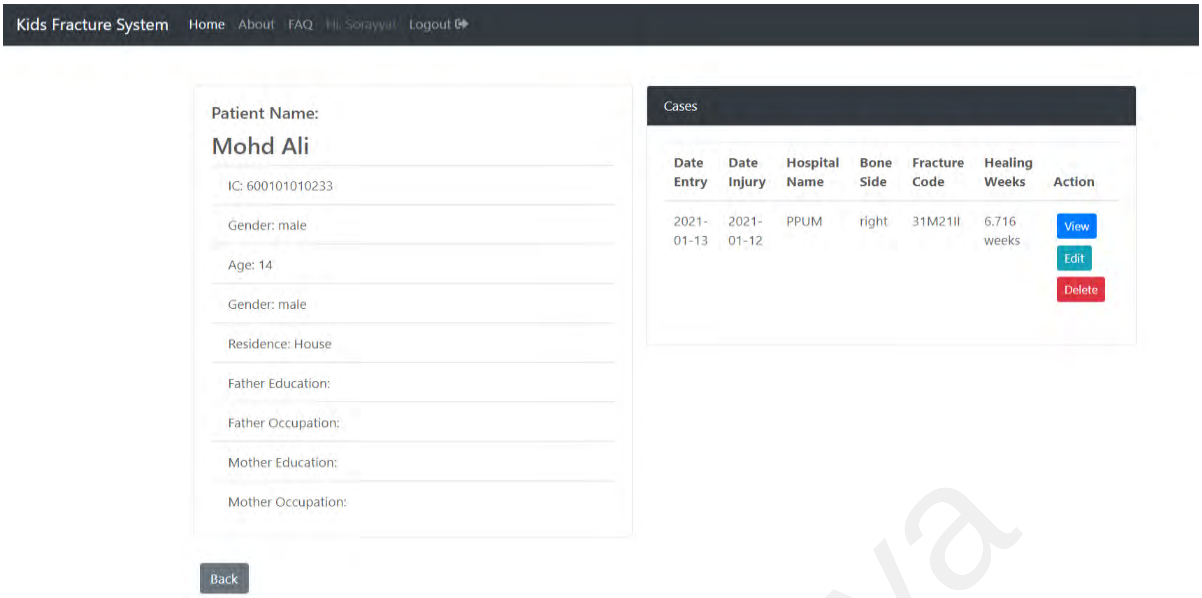


Figure 4.32: Result page that shows the patient information according to case and the predicted healing weeks is shown.

The 'Cases' information regarding the fracture cases that the user had saved into the system. User can 'view', 'edit' or delete specific cases on this page. This allows the user to have a clear view of the patient and the healing weeks of the fracture are also displayed as shown in Figure 4.33.

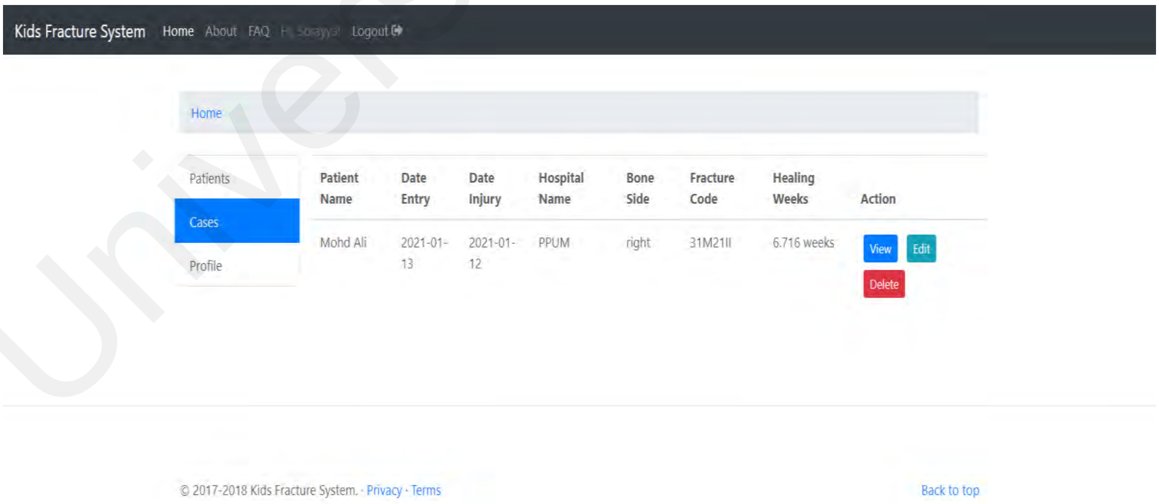


Figure 4.33: Once Patient Fracture Case was successfully added into the Kids Fracture Expert System, the dashboard able to view the added case and perform various functions.

4.2.5 Kids Fracture System Profile Tab

The user of this system is mostly doctors and orthopaedics. Under the 'Profile' tab, the user can edit their personnel information as well as the hospital name and doctor registration number. Once all the information is updated, the user has to click the 'Save' button, the data will automatically be updated into the database. The interface is shown in the figure 4.44 below.

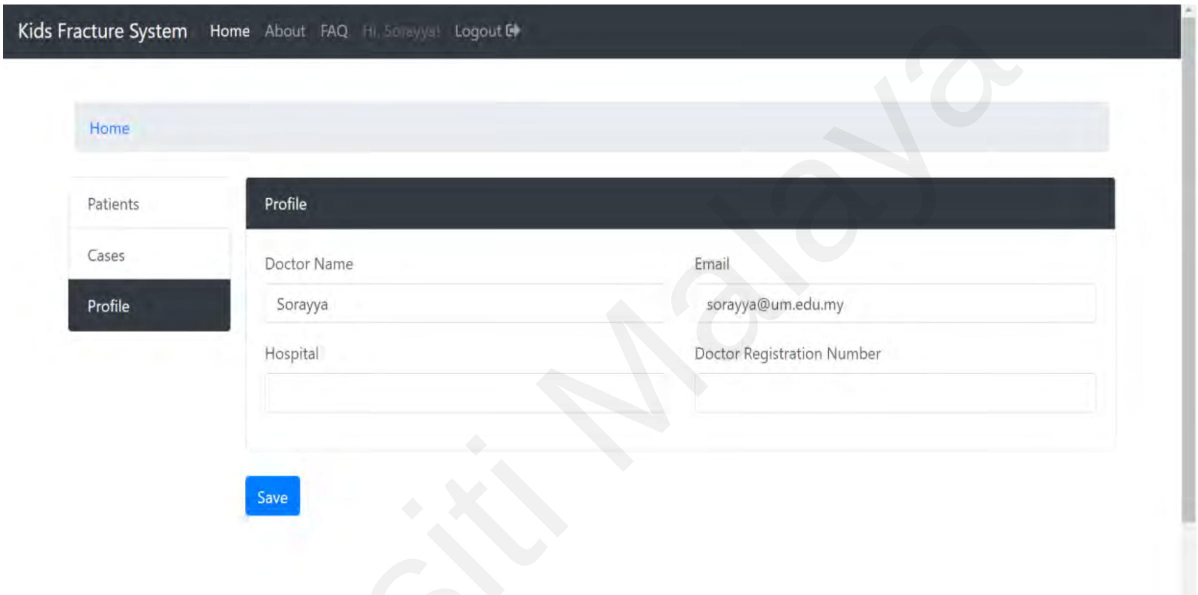


Figure 4.34: Kids Fracture System Profile Tab

4.2.6 Kids Fracture System Detailed Case

The page shown in Figure 4.45 is the detailed view of the fracture injury together with the predicted fracture healing time and the expert suggestion treatment for the injury. The images of the bone involved, segment of bone is also display to the user.

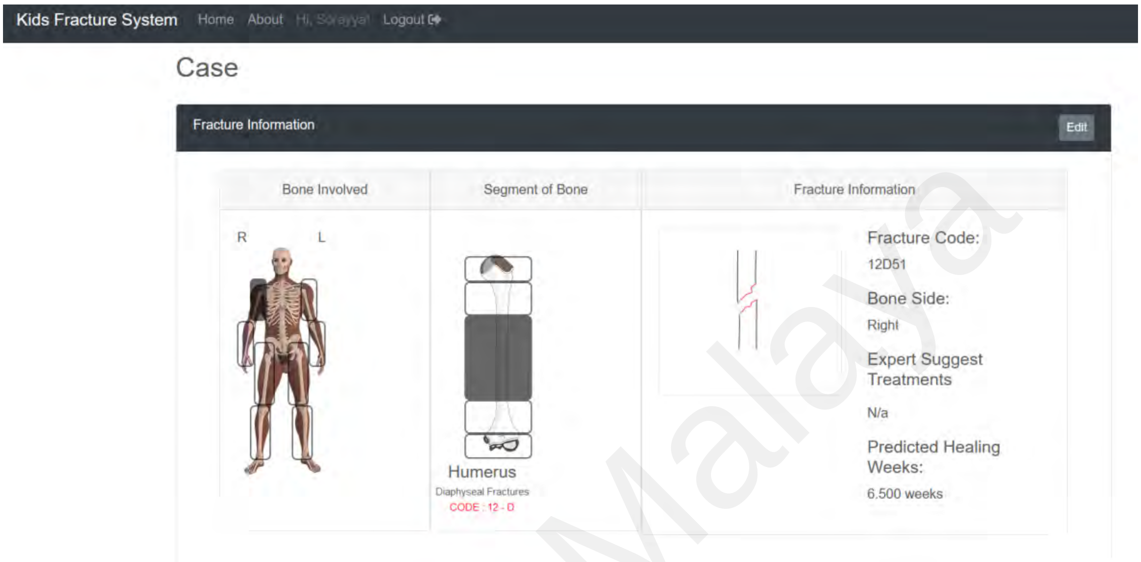


Figure 4.35: Kids Fracture System Detailed Case with Expected Healing Time and Expert Suggest Treatment.

4.2.7 Overview of Kids Fracture System

Under the ‘Overview’ tab, contains information of the expert system. Users can explore the ‘About’ page as shown in Figure 4.45. Details including the overview of the system, classification system: according to location and classification: according to morphology. Users can access to these tabs and read more about the fracture system.

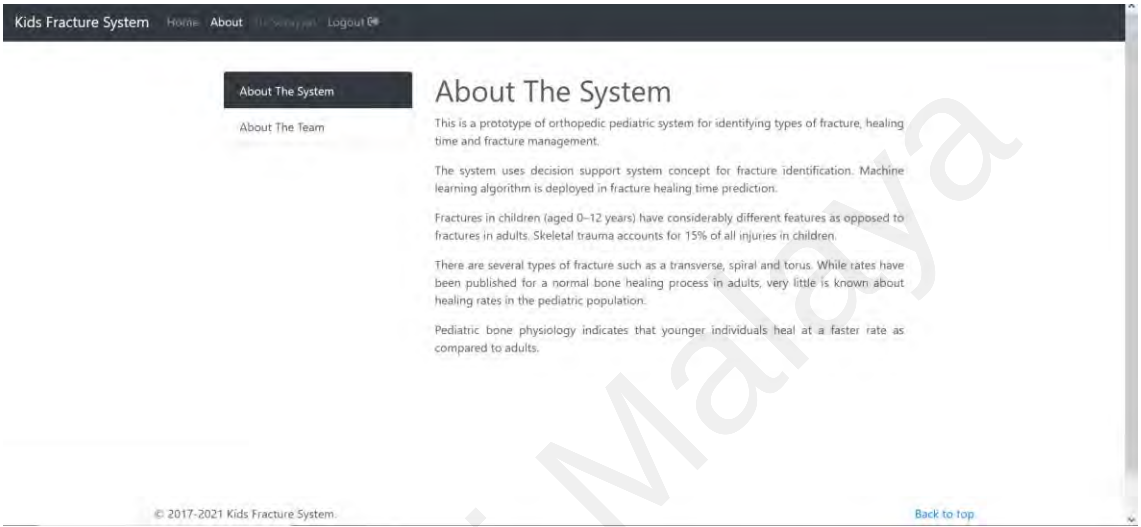


Figure 4.36: An overview page for the overall concept of the expert system.

4.4 System Usability Testing (SUS)

The evaluation form is created based on the System Usability Scale (SUS) which comprises 10 questions to assess the usability and functionality of the website. The system usability evaluation form is given in the form of Google Forms to several users that are related to the research, such as;

- Paediatric orthopaedic
- General orthopaedic
- General medical practitioner
- Healthcare worker and Nurses
- Administrative staffs
- Researchers and students

The pie chart in figure 4.46 illustrates the demography of the respondent designation. Overall, healthcare worker made up of 45.5% in the respondent designation, however, general orthopedic, pediatric orthopedic and others comprise of 9.1% of the whole chart.

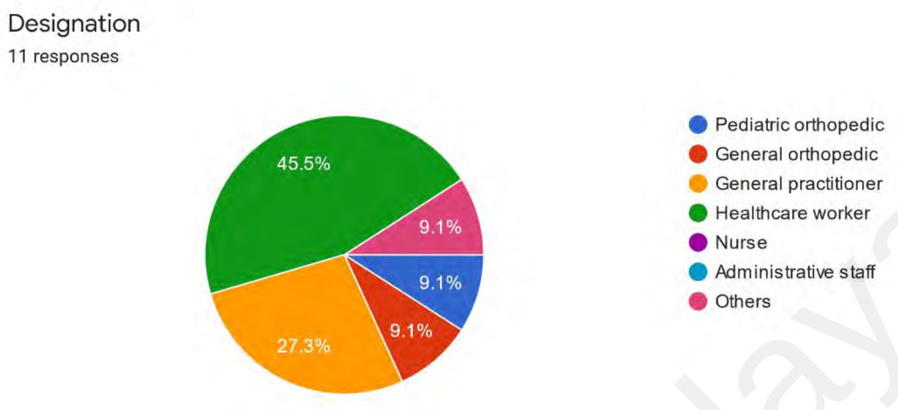


Figure 4.37: Pie Chart of the Respondent Designation.

The results from the SUS questionnaire created in Google Form, the responses are collected and the bar charts below shows the responses for each question from the SUS questionnaire.

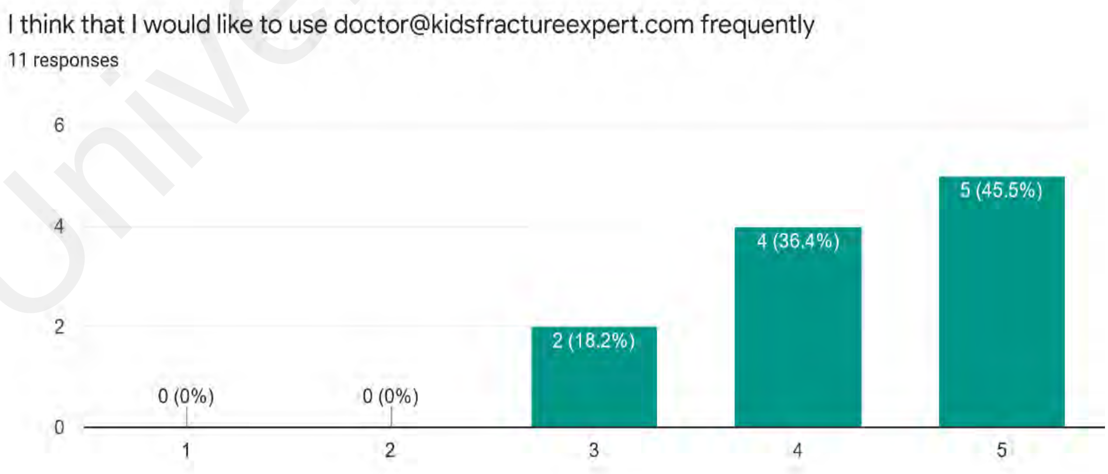


Figure 4.38: SUS Question 1 outline the question of "I think that I would like to use doctor@kidsfractureexpert.com frequently". From the bar chart above, majority gives positive responses as they would like to use the system.

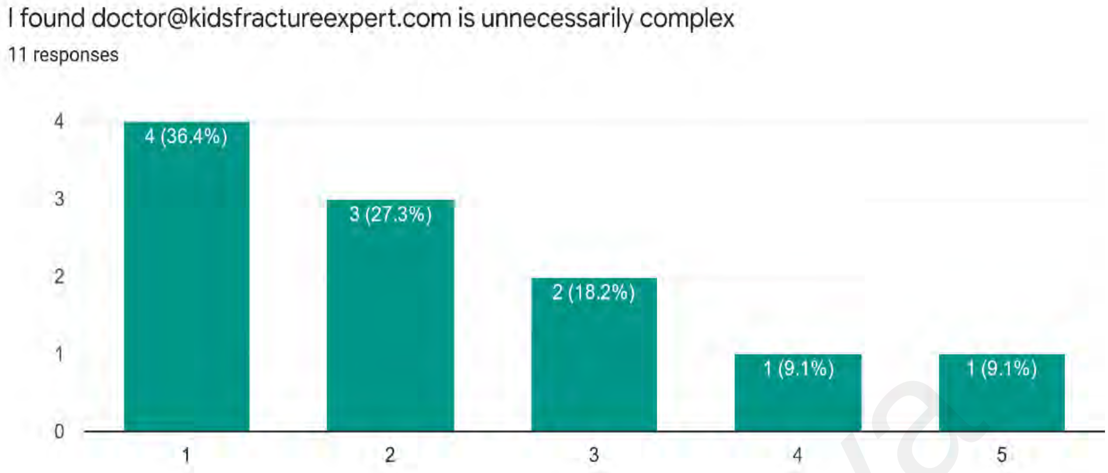


Figure 4.39: SUS Question 2 describes that "I found doctor@kidsfractureexpert.com is unnecessarily complex" of all 11 responses 36.4% stated that they disagree with the statement.

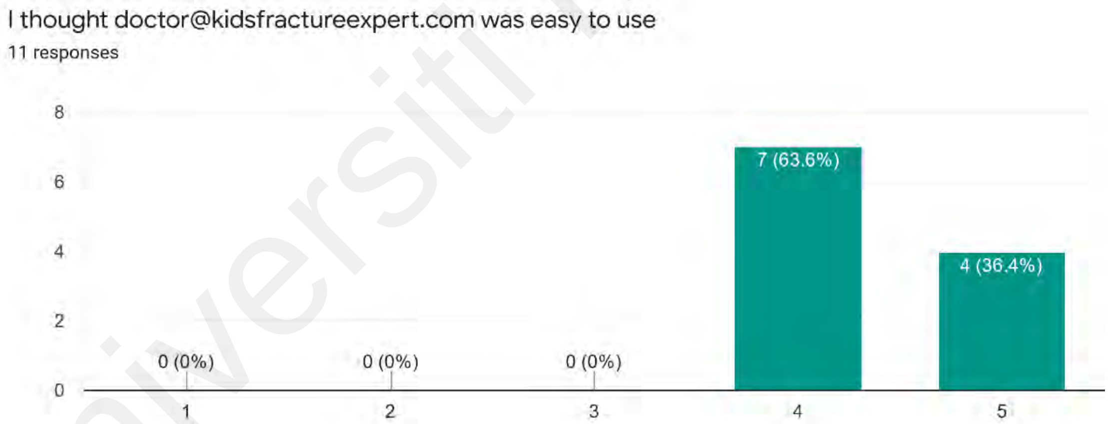


Figure 4.40: Question 3 describes that "I thought doctor@kidsfractureexpert.com was easy to use". All the responses stated that the system was fairly easy to operate.

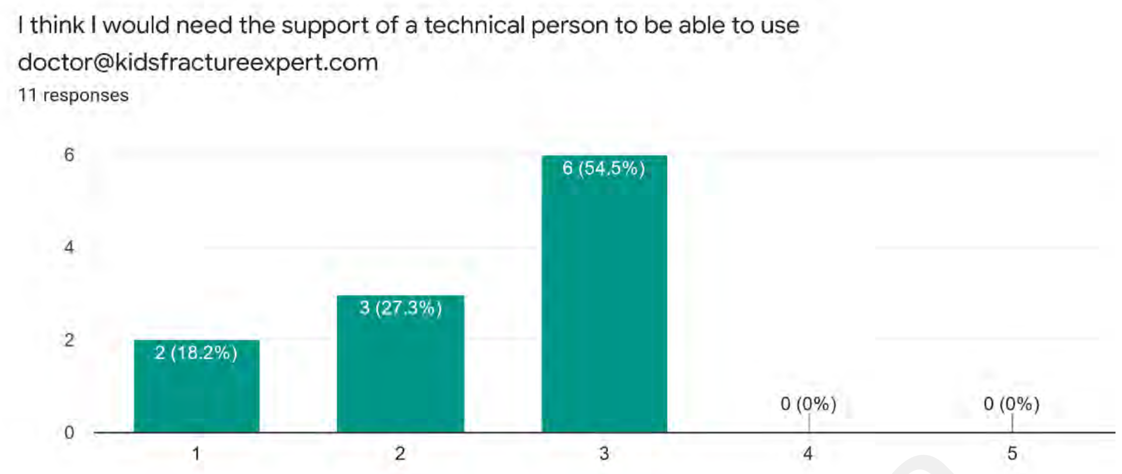


Figure 4.41: Question 4 states that "I think I would need the support of a technical person to be able to use doctor@kidsfractureexpert.com". Most of the responses remains at the average, and a few respondents respondeded disagree with the above statement.

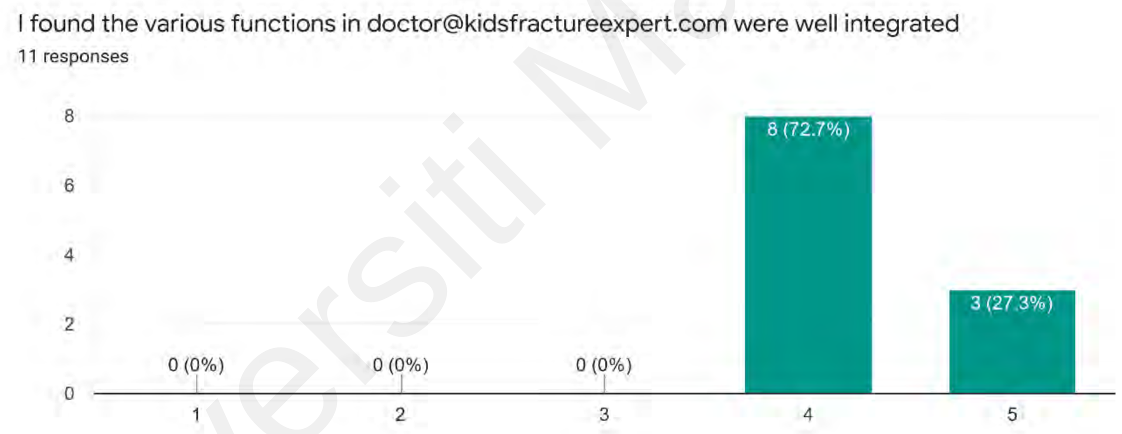


Figure 4.42: Question 5 is "I found the various functions in doctor@kidsfractureexpert.com were well integrated". All the respondents agree with the statement.

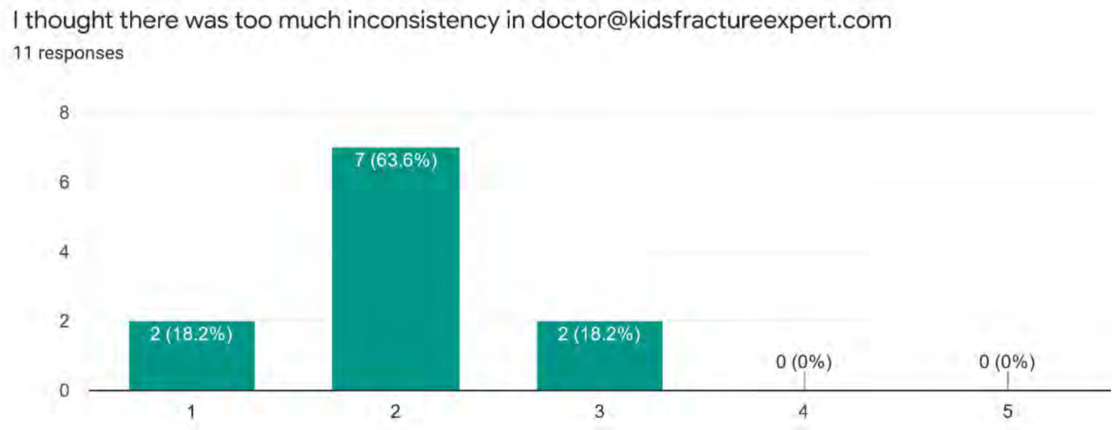


Figure 4.43: Question 6 states that "I thought there was too much of inconsistency in doctor@kidsfractureexpert.com". Majority of the respondent choose "2" which disagrees with the statement.

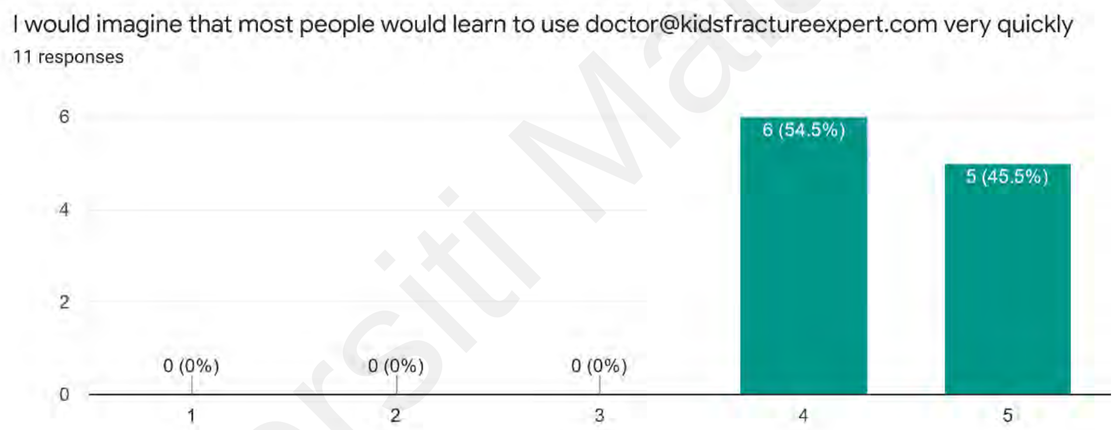


Figure 4.44: Question 7 describes that "I would imagine that most people would learn to use doctor@kidsfractureexpert.com very quickly". All the respondent responded positively with the statement.

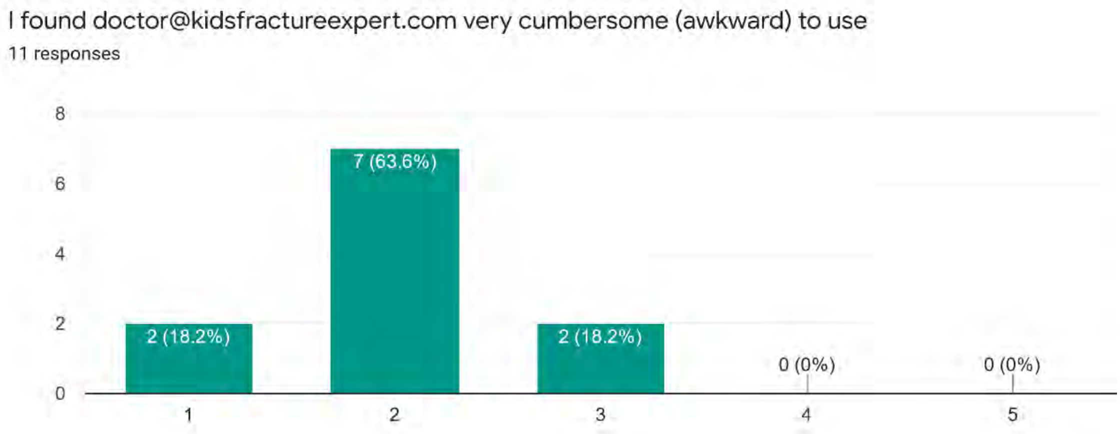


Figure 4.45: Question 8 describes "I found doctor@kidsfractureexpert.com very cumbersome (awkward) to use. 9 out of 11 responses shows disagree with the statement, where 2 of the respondents remains neutral with the question.

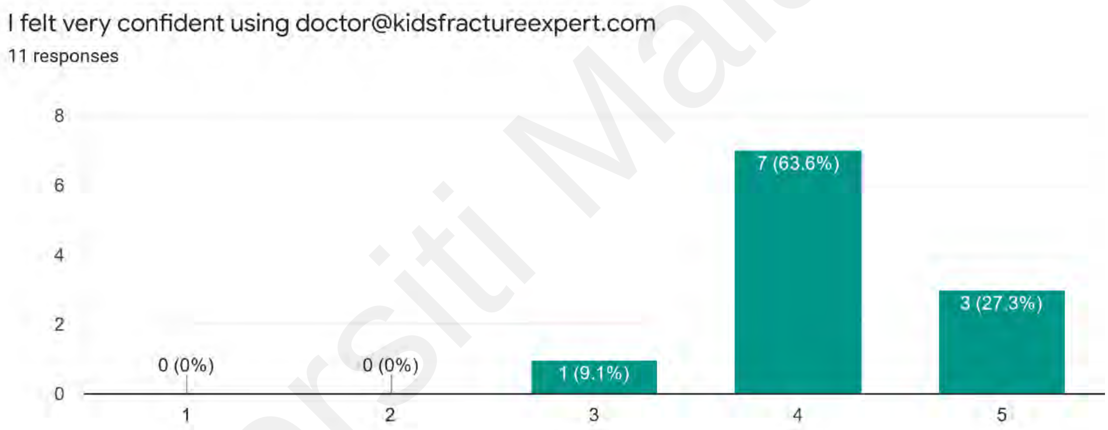


Figure 4.46: Question 9 states "I felt very confident using doctor@kidsfractureexpert.com". Greater part of the respondents response "agree" with the statement as they are statisfied with the system.

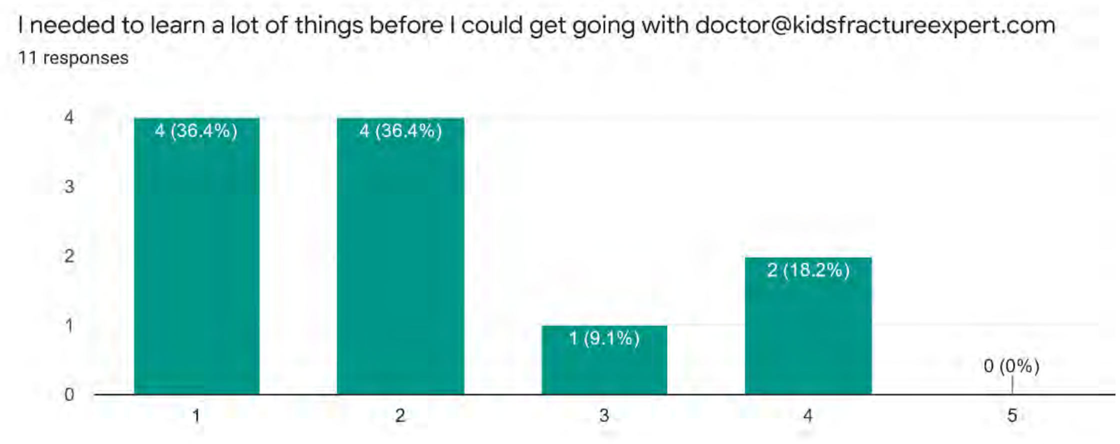


Figure 4.47: The last question, Question 10 states "I needed to learn a lot of things before I could get going with doctor@kidsfractureexpert.com". Minority of the responses remains "neutral" and "disagree" with the question, as they most probably required to study

The scores are then converted into numbers and calculate the usability score using SUS. The outcome of the calculated score is average at the SUS score of 80, consider as “Good” according to the SUS score shown in figure 4.57, which falls under the acceptability range.

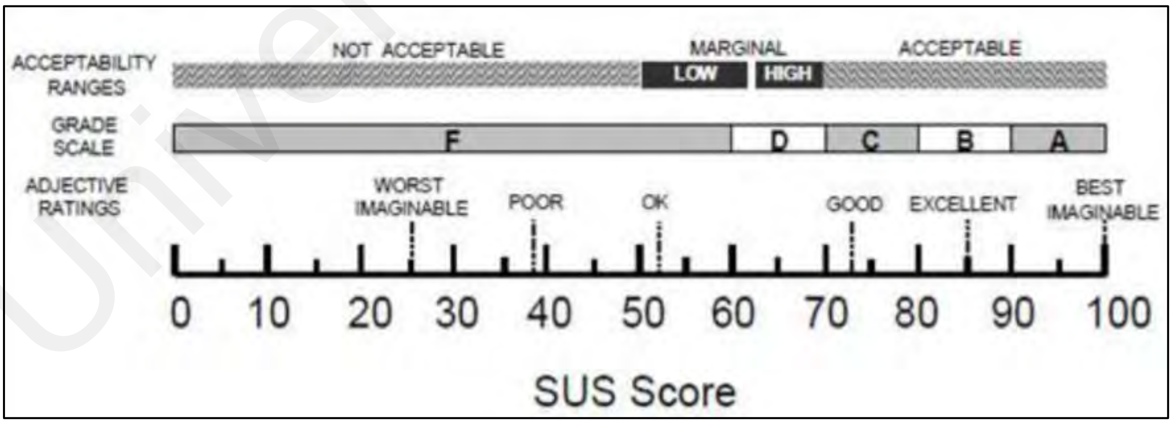


Figure 4.48: SUS scores Grade Rankings from “Determining what individual SUS scores mean: Adding an adjective rating scale.” (Bangor, Kortum, & Miller, 2009)

From the result indicates that the system is acceptable and could be used by medical practioners especially peadiatric orthopeadics. The excel sheet shown in Figure

4.49 is the outcome of the calculation of the SUS Score, including the users demographic and also comments towards the system shown in Figure 4.50. The respondents could be increase in the near future time, as this study developed a system prototype. The system could be upgraded with better user interface and also a better prediction model.

Name	Organization	Designation	I think t	I founc	I thou	I thi	I four	I thoug	I wo	I four	I felt	I nee	Comments for improvement:	SUS Raw Score	SUS Final Score
Zuhri Md Yusoff	HPUPM	General orthop	4	2	4	3	4	2	4	3	4	3	suggest for tickboxes for mechanism injury and data	27	67.5
Roshan Gunalan	Subang Jaya Medical Centre	Pediatric ortho	5	5	5	2	4	2	5	1	5	1	Good work	33	82.5
Siti intan syafina	KKM	Healthcare wo	5	1	5	1	5	2	5	1	5	1	-	39	97.5
Shafiq	UiTM	Healthcare wo	4	4	4	3	4	2	4	2	4	2	User friendly. Easy to use and interprete	27	67.5
Azri Fikry	Putra Specialist Hospital Melaka	Healthcare wo	5	1	4	2	5	1	5	1	5	1	-	38	95
sazzli	uitm	Healthcare wo	4	3	5	2	4	2	5	2	4	2	its ok	31	77.5
Aida	Universiti Pertahanan Nasional Malaysia	General practit	5	2	4	3	4	2	4	2	4	4	Excellent	28	70
Liew Kong Fui	Liew Clinic	General practit	3	2	4	3	4	3	5	2	3	2	Nil	27	67.5
Dr. Michael Gan	Kairous Capital	Others	3	1	5	1	5	1	4	2	4	1	Good research work	35	87.5
Leonard Leong S	Ministry Of Health	General practit	5	1	4	3	4	1	5	2	5	1	-	35	87.5
Dr. Chuah Ting S	BP Healthcare	Healthcare wo	4	1	4	2	5	2	4	2	4	2	-	32	80
															80

Figure 4.49: SUS Score calculation towards the system.

Comments for improvement:

11 responses

-

suggest for tickboxes for mechanism injury and data

Good work

User friendly. Easy to use and interprete

its ok

Excellent

Nil

Good research work

Figure 4.50: Additional Comments for kidsfractureexpert.com

CHAPTER 5 - CONCLUSION

Machine learning methods have proven their capability in predicting upper-limb fracture healing time. This study designed an efficient and useful tool for paediatric orthopedics, where this research looks into the viability of merging machine learning algorithms like Support Vector Regression (SVR), Random Forest (RF) and Self-Organizing Map (SOM). With the well-developed model, it can be applied into an online expert system to support paediatric orthopedist by giving advise and suggestion estimating the rate of fracture healing.

It may be concluded that employing such a map in conjunction with fracture presentation may be a helpful screening technique for finding children at risk of blocked prolonged healing period, which may necessitate particular care. The fracture presentation can serve as a clinical guideline to the attending doctor as to the expected healing times of fractures. A comprehensible guideline is given as to the rate of healing and subsequent return to premorbid function for the children. However, it is not possible to claim the results at this stage as the results might has universal application. Even though it is based on limited clinical data, this research can be a useful tool for placing a patient within a clinical context, allowing clinicians to reach consensus, assessing the particular risk to a patient, and monitoring their progress under treatment if used within a validation system and continually recreated as more data is collected.

It can be concluded that machine learning algorithms like SVR, RF and SOM techniques can access the upper limb fracture healing time for variable selection and prediction among paediatrics. The lower limb fracture healing rate could be evaluate through RF method for regression tree and SOM algorithm. However, additional research is necessary to further improve the machine learning algorithm performance and the models created ever since that the application of RF and SOM seems have still not developed into its full potential especially in the fracture healing rate among children. It still need to be validated externally by using different machine learning methods such as Support Vector Machine. Moreover, machine learning methods applications are not yet fully developed especially in paediatric fracture healing.

Several recommendations and enhancements could be made to improve the model's performance and efficiency, including the system's usability. As the system developed is more focused on paediatric patients, in the near future, provided with the data availability for adult patients, future add-ons on predicting fracture healing time for adult patients can be added into the system. Besides, improve in the data imputation, since the data with missing values have been removed, eventually decreases the number of training and testing dataset. There, data imputation should be applied as it will not affect any medical obtained and it provides a large dataset for the model to train in order to recognize all the patterns that able to classify groups accurately. Thus, it will improve the performance of the machine learning model.

Further studies are needed to refine its performance and more predictive models need to be developed to compare better performance. Moreover, models developed in this study still need further validation. Based on the results, SVR produces optimum results compared to the RF model for the upper limb fracture data. However, SVR and SOM models demonstrate their applicability as a very effective method for identifying the most relevant factors and forecasting fracture healing time. There was no study done in the paediatric orthopedic field, therefore it was hard to refer to or to be guided to other research and thus this work is considered to be original.

Overall, there were a lot of knowledge gained throughout the model and system development. It includes the depth understanding of machine learning on R, scripting programming language, database management system, software development methodology and health informatics in general.

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