DEEP LEARNING BASED ADVANCE IMAGE PROCESSING FOR BONE FRACTURE DETECTION

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"DEEP LEARNING BASED ADVANCE IMAGE PROCESSING FOR BONE FRACTURE DETECTION"**, submitted by **Md. Saim Islam** and **Syed Asif Rahman** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13th July, 2024.

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We hereby declare that this project has been done by us under the supervision of **Mushfiqur Rahman, Lecturer (Senior Scale), Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Bone fractures are widespread in different age groups; hence, making the medical interventions more effective and accurate demands the application of the most precise diagnostic techniques. The traditional procedures for the detection of fractures typically involve many errors and are labor-intensive because a doctor has to do interpretation of the radiography scans. This study proposes the use of deep learning-enhanced image processing system as an automated system to overcome the aforementioned difficulties in bone fracture detection. The system enhances and boosts the fracture diagnosis accuracy by using the latest methods, such as convolutional neural networks (CNNs). A systematic way begins with a number of annotated datasets of medical images that ranges from X-rays, CT scans to MRIs. CNNs are trained to identify features of fractures, whereas preprocessing steps aim at size normalization and image quality improvement. Hyperparameter tuning enhances the model's performance through the dataset division into the training, validation, and testing parts. The measuring standards like precision and accuracy justify the validity of the model. Healthcare professionals can be absolutely certain about practical implementation by an easy integration in current healthcare systems and also with a creation of an intuitive interface. The project takes into account the scalability, the ethical issues, and the regulatory compliance. The goal is to create such a system that exponentially boosts the accuracy, speed, and efficiency of fracture recognition in the medical field, where the damage of bones is prominently diagnosed.

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CHAPTER 1
INTRODUCTION

1.1 Overview

The bone fracture is a condition in which the bone becomes cracked or broken, usually as a result of trauma, like accidents, falls or sports injuries. Fractures might be can be classified into different degrees of severity: from a fine crack to a complete bone disruption. Without doubt, the only two factors, namely, whether the injury is caused by “soft sounds” or by “sharp surfaces” and the severity of the break actually matters in the medical diagnosis and in the design of the treatment plan. The dataset comprises a collection of images categorized into two classes: The question is "Crushed" and "Not crushed". Altogether the research has 4840 photos labeled as broken and an extra 4623 ones labeled as unbroken. "A bone which is broken in half is well seen on the chart. It is compared to a bone which is not broken". In a simple word, the data set is a golden resource for training and evaluation of devices that are developed to diagnose bone fracture in medical images through machine learning. The advancement of the diagnosis of fractures and patient care will also be the gift of this, together with the research and development of computer vision, medical imaging, and healthcare technology. A topic of my research paper focuses on the use of deep learning to detect bone fractures by means of progressed image processing methods. Firstly, it was split on collections of bone X-ray images in our research and make a decision to utilize both MobileNetV2, DenseNet201, Xception and Hybrid model (MobileNetV2 and Xception) network models for examining fractures. The models present a detailed and precise method for images analysis and detection of injuries with a very high accuracy rate. The primary objective of this engaging investigation is to examine the quality of the MobileNetV2, DenseNet201, Xception and Hybrid model (MobileNetV2 and Xception) models in having the ability to identify bone fractures and to show that they are useful for diagnosis in real time. The models right exhibiting the extremely accuracy rating ratios that are ranged from 98%93% to 99%. 13% (X) and 13% (Y) are the impressions of the fact that the AI algorithms for interpretation of X-ray images fractures are very practical and precise.

1.2 Background and Present State

The medical diagnostics technology advancements through cutting-edge technologies are an unwavering journey with the hope of improving patients' care and consequently the global health outcomes. In the area of orthopedics, exact and timely detection of bone fractures plays the major role in the correct treatment and rehabilitation process.

The title "Deep Learning-Based Advanced Image Processing for Bone Fracture Detection" symbolizes a strong determination to use the latest technologies to solve this problem. Transfer learning, the underlying paradigm for artificial intelligence, is the basis for this research. The power of the transfer learning comes from the fact that knowledge gained from unrelated tasks is being reused, allowing the model to detect bone fractures in far more efficient manner than before. The use of deep learning architectures, particularly MobileNetV2, DenseNet201, Xception and Hybrid model (MobileNetV2 and Xception), shows the technological capability that is behind this research. By exploring non-invasive detection strategies in detail, this work does not only intend to detect bone fractures, but also to provide a complete picture of the affected zones. Those insights are priceless for personalized treatment plans and maximizing the patients' outcomes. Through this tremendous comparison, the study tries to find out the best strategies for bone fracture detection which will change the diagnostic practices and will raise the standard of orthopedic care globally.

1.3 Problem Statement

The timely and accurate detection of bone fractures is a crucial component of orthopedic diagnostics and patient care, and it is the main problem this study attempts to address. It is still very difficult to reliably and efficiently identify fractures, even with improvements in medical imaging technologies. The goal of this work is to improve the accuracy and dependability of bone fracture detection in X-ray images by utilizing deep learning, specifically with the use of MobileNetV2, DenseNet201, Xception and Hybrid model (MobileNetV2 and Xception) network models. The goal is to create a reliable and accurate method for evaluating medical images, which will eventually enhance orthopedic patient outcomes and diagnostic procedures.

1.4 Objectives

The more pressing issues confronted by imaging and diagnostics in the field of orthopedics nowadays are more than those that have been faced before which is why this study about “Deep Learning-Based Advanced Image Processing for Bone Fracture Detection” is so important. There would be no doubt that the bone fracture is the main health problem that it is necessary to find out the method of discovering them as soon as possible. With respect to the concerns of deep learning methods, the algorithmic transformation of MobileNetV2, DenseNet201, Xception and Hybrid model (MobileNetV2 and Xception) Neural Networks cannot be ignored and these methods would be critical to take the classifier to the next level. One of the salient parts of the artificial intelligence is transfer learning that is very instrumental to the system of AI by the use of the previous experiences in the unrelated tasks. Therefore, the model is capable of not just getting to recognize the fracture in the X-ray pictures but also in teaching how to differentiate between the different kinds of fractures. The advantage of consideration of CNN in the research is that CNNs are highly efficient in image analysis and accurate as well. This work does not include only the discussion of the topic of which architecture or method is the best for the detection process, but it is also about how the evaluation of different architectures is done. The MobileNetV2 and DenseNet201 models have strengths and weaknesses in failure detection; they should be known well so that the model can be used to its maximum potential and medical stuff makes accurate decisions. The research project aims at investigating the latest and, consequently, the next generation of orthopedic diagnostic tools and hopefully gives the scientists a fruitful insight of the methods involved in fracture detection, as well as of various deep learning techniques.

1.5 Scope and Limitations

This work addresses the problem of bone fracture detection in medical X-ray images through the application of deep learning techniques, specifically transfer learning with MobileNetV2, DenseNet201, Xception and Hybrid model (MobileNetV2 and Xception) architectures. Included in the scope are the labelled X-ray image collection and classification, the training of the chosen neural network models, and an assessment of the models' accuracy and usefulness for real-time diagnostics. The study is constrained, though, by the inherent unpredictability of medical images, possible biases in the dataset, and the requirement for high computing power for model evaluation and training. Furthermore, even though the models are designed to attain high accuracy, the research recognizes that no diagnostic tool can provide 100% precision, and that in order to provide effective patient care, the models must be integrated with clinical expertise.

1.6 Report Organization

I strictly have a format this report follows to make it understandable to the reader taken through the research process, findings as well as implications. The role of each section is specifically defined accordingly, the space for each being deliberated to strengthen the document as a whole.

Chapter 1: Introduction

The chapter firstly informs the reader about the research and underlines the significance of the Bone fracture detection, the usability of transfer learning, deep CNNs, and the need of comparison study between detection and segmentation methods. This involves presenting the research questions, objectives, and the general picture of the whole study.

Chapter 2: Literature Review

Article's background sub-section includes extensive information about the selected research literature and relevant studies' review. In this part, the author profoundly discusses the theoretical basis and methodological models that are connected to the application of Bone fracture detection, transfer learning, and deep convolutional neural networks. For that reason, it constitutes the grounds for the research topic defense and the gaps in the existing knowledge are outlined.

Chapter 3: Methodology

In the research methodology chapter, the authors describe the method they used to carry out the study. It suggests in detail the research design, the data collection method, the model architecture, and why the methodologies chosen were specifically suitable. The chapter further talks about the ethical factors that might interlinks with the study and the possibly limitations.

Chapter 4: Implementation

In this chapter the study uses a sophisticated framework integrating cameras, Python programs, databases, and a web application. It requires high-performance hardware and advanced software, including transfer learning with pre-trained CNNs and a hybrid model. The web application allows medical professionals to upload X-ray images, demonstrating the feasibility and benefits of transfer learning and model fusion for practical applications.

Chapter 5: Result and Analysis

This chapter offers the experimental results which have been gained from the use of transfer learning and deep CNNs in the detection of Bone fracture. Comprehensive analysis of different roles that detection and segmentation play is presented. The visual representation and statistical measure play in validating the results are discussed as well.

Chapter 6: Impact On Society, Environment and Sustainability

The societal impact chapter is dedicated to the study of healthcare and medical diagnostics foundation research findings in the ambient context. It explores how a new Bone fracture detection approach highly impacts the quality of care and treatment outcome, leading to the improvement of public health level. Regarding the future technology and its possible social impacts, tech is seen as a key player.

Chapter 7: Conclusion And Future Work

This final chapter presents the essentials of the report as a whole. It is the final part of the write-up which gives crystallized version of core findings, reconfirms conclusions based on research and put together practical applications which can be implemented and possible areas that are may extended further studies. The issues for future research are mentioned, thus a roadmap for researchers who would like to continue the current study is given.

This confirms a process of clear thinking that provides the reader with a fundament of arranged information that begins with the introduction and ends with the broader implications and recommendations. Together, it gives a complete insight into the methodology and outcome research of Bone fracture detection and screening with transfer learning and deep CNN.

1.7 Summary

This study examines the utilization of deep learning methods for the precise and prompt identification of bone fractures in medical X-ray pictures, which is a critical component of orthopedic diagnosis and patient treatment. The study seeks to improve the accuracy and precision of fracture identification by using the MobileNetV2, DenseNet201, Xception and Hybrid model (MobileNetV2 and Xception) network models. This will be done by analyzing a large collection of X-ray images that have been labelled. The research highlights the importance of transfer learning, which enables these models to efficiently analyze and detect fractures by leveraging knowledge from unrelated tasks. The study focuses on the persistent difficulty of consistently reaching high accuracy in fracture identification, despite the progress made in medical imaging technologies. It showcases the capacity of these deep learning models to revolutionize diagnostic procedures and enhance patient results. The coverage encompasses the processes of model training, evaluation, and a thorough comparison of the advantages and disadvantages of MobileNetV2 and DenseNet201. Nevertheless, the study also recognizes constraints such as the inconsistency of medical imaging, possible biases in the dataset, and the requirement for significant computational resources. The project aims to contribute to the development of advanced orthopedic diagnostic tools, providing vital insights into the effectiveness of deep learning approaches in medical imaging.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The clarify of this challenging issue can be ensured and a comprehensive understanding of the groundwork of the study area could be facilitated through the investigation of "Deep Learning-Based Advance Image Processing for Bone Fracture Detection"-related terms and concepts. Learning transfer mechanism which plays a primary role in the area of artificial intelligence provides us with the foundation for the practical implementation of this project. It is the process of exploiting the knowledge and the insights which are obtained from one task or domain and applying them to another related task or domain. In the context of fracture detection, transfer learning allows the model to capitalize on previously known knowledge and patterns acquired from unrelated operations, which results, in increased ability of the model to accurately detect fractures in medical images. Deep Convolutional Neural Networks (CNNs), which are a subfield of the image analysis and machine learning, constitute one of the fundamental pillars. The neural networks are designed for spotting the patterns and features in visual data, which makes them perfect for tasks like image detection and segmentation. Dense CNNs operating on X-ray pictures with regard to the fracture detection determine with great precision the areas signifying of bone fractures. Identification and positioning of entities and abnormalities that are in the image is what detection is all about. In the case of the detection of bone fractures, detection is the process of identifying the presence of fractures in the X-ray images. The next technique, 'segmentation', means to put a box or to outline the border around a specific area or objects within the picture. Segmentation process allows to isolate the fracture-affected parts with high accuracy and may give useful information about fracture configurations and anatomical location.

2.2 Related Works

Using deep learning-based computer vision algorithms, Erzen, E. M. et. al. (2023) proposed an automatic end-to-end computer-aided diagnosis (CAD) system for bone fractures in pediatric wrists. The objective was to simultaneously detect and classify different pediatric wrist injuries, such as fractures, soft tissue abnormalities, metallic artifacts, and bone anomalies. The CAD system was trained and assessed with YOLOv8, an advanced object detection model, using the GRAZPEDWRI-DX dataset. Promising precision (77.80%), recall (54.60%), (59.10%), and (37.20%)

were demonstrated in the experimental results, suggesting potential improvements for precise prediction of pediatric wrist fractures in healthcare settings. [1]

Sahin M. E. (2023) utilized a dataset containing both normal and broken bones to tackle the issue of misdiagnosed or undetected bone fractures. Various machine-learning techniques, including X-ray image preprocessing and feature extraction methods such as Canny and Sobel edge detection, Harris corner detection, and Hough line detection, were employed in this study. The primary objective was to develop a computer-aided diagnosis (CAD) system capable of accurately identifying fractures to alleviate the workload of healthcare providers and enhance diagnostic accuracy. The extracted features were input into twelve machine learning classifiers, and the results were systematically organized. The results of classifier comparison revealed that linear discriminant analysis (LDA) emerged as the most successful classifier, boasting an accuracy rate of 88.67% and an AUC of 0.89. These findings underscore the effectiveness of LDA in fracture detection and highlight the careful methodology employed in the investigation. [2]

In a study published in 2023, Inam, Islam et. al. discussed the shortcomings of automated systems for crack identification. The objective was to present a deep learning-based, two-phased framework for managing smart infrastructure. YOLOv5 models (s, m, and l) were used in the first phase to detect cracks, and they performed exceptionally well, with mAP values of 97.8%, 99.3%, and 99.1%, respectively. Using the U-Net model, crack segmentation was done in the second phase by measuring each pixel's width, height, and area. [3]

A deep-learning-based neural network was optimized in 2022 by Marwa et. al. for automatic segmentation in Ultrasonic Computed Tomography (USCT) bone images within the ultrasound domain. Using a VGG-SegNet neural network for bone segmentation, the study improved the Variable Structure Model of Neuron (VSMN) for USCT noise removal and dataset augmentation. The researchers created a new USCT dataset, and the model they built, which used both CPU and GPU, did better than previous models, with 97.38% accuracy in training and 96% accuracy in validation. The model outperformed existing state-of-the-art techniques in its ability to augment USCT data and autonomously segment bone structures, exhibiting high segmentation accuracy with a minimal error of 0.006 during testing. [4]

Tanzi et al.'s (2020) study aimed to evaluate and analyze papers that used different deep-learning techniques to find and classify bone fractures. The authors chose representative studies to identify strengths and develop a generalized strategy. Area under the curve (AUC), test accuracy, sensitivity, specificity, dataset size, and labeling reliability were among the assessment parameters. The study highlights the significant contribution of deep learning, specifically convolutional neural networks (CNN), in obtaining outcomes that are on par with human abilities. The main objective was to aid in the creation of a solid computer-aided diagnosis (CAD) system that would support doctors effectively and reduce diagnostic errors. [5]

With Ouyang et al.'s (2023) study, the authors wanted to use design thinking to create and improve a deep learning (DL) algorithm that could help with clinical problems. To decrease the number of femur fracture misdiagnoses made using pelvic plain film (PXR), the study gathered 4235 PXRs. It created DL detection models using the Xception convolutional neural network (CNN). The algorithm's diagnostic accuracy increased from 0.91 to 0.95, sensitivity from 0.97 to 0.97, and specificity from 0.84 to 0.93 with the incorporation of design thinking. This study highlighted the importance of using a user-centered design thinking approach to optimize deep learning solutions to meet the needs of patients and healthcare providers. [6]

Tanzi et al. (2020) used 2453 labeled images of the proximal femur to create a Deep Learning tool for bone fracture diagnosis. They made use of an enhanced InceptionV3 CNN and a multistage CNN architecture. The tool's average accuracy for three classes was 0.86, and for five classes, it was 0.81. It benefited students and increased specialists' accuracy by 14%. The instrument is intended to cover every bone segment in typical hospital procedures. [7]

Kong et al. (2022) used deep learning and long-term data to create an X-ray-based fracture prediction model. 1,595 people between the ages of 50 and 75 who had lumbosacral radiographs done at Seoul National University Hospital between 2010 and 2015 were included in the study. The convolutional neural network-based prediction algorithm DeepSurv performed better in the test set with higher C-index values. The model demonstrated better performance without any clinical characteristics, especially in the cohort of women, which comprised 74.4% of the participants. During the 40.7-month follow-up period, on average, 7.5% of participants suffered from vertebral fractures. [8]

The study evaluated a deep learning algorithm for detecting and classifying proximal humerus fractures in shoulder radiographs. A deep convolutional neural network (CNN) was trained on 1,891 images, showing high performance in distinguishing normal shoulders from fractures and classifying fracture types. The CNN achieved 96% top-1 accuracy, 1.00 AUC, 0.99/0.97 sensitivity/specificity, and 0.97 Youden index in distinguishing normal shoulders from fractures. It also showed promising results in classifying fracture types, with 65-86% top-1 accuracy and a Youden index of 0.71-0.90. According to a comparative analysis with human groups, CNN outperformed general physicians, orthopedists, shoulder-specialized orthopedists, and particularly in complex fractures. [9]

Deep learning and data augmentation were used in a study to detect and reliably classify fractures of the femur neck. The researchers applied ground truth labels on 1,063 AP hip radiographs from 550 patients and digitally reconstructed radiographs from preoperative hip CT scans and generative adversarial networks. The deep neural network was designed and fine-tuned using a twenty percent validation group. The accuracy of the two-class prediction of fracture versus no fracture was 92.3%, and the accuracy of the three-class prediction of Garden fractures was 86.0%. [10]

The study aimed to create an automated deep-learning algorithm for classifying radiographs based on the new AO/OTA 2018 ankle fracture standards. The AO/OTA 2018 classification system was used to categorize 4,941 radiographic ankle examinations, which comprised the dataset. Utilizing a test set of 400 patients, the neural network built on the ResNet architecture was assessed. The neural network accomplished the correct AO/OTA class classification with an average area under the receiver operating characteristic curve (AUC) of 0.90. AUC of 0.93 was highest for malleolar type B fractures, whereas malleolar A fractures performed the lowest. [11]

The project aimed to diagnose and treat wrist fractures in hospital emergency services more accurately by applying deep learning to wrist X-ray images. Using various object detection models, a dataset from Gazi University Hospital was subjected to 20 distinct fracture detection procedures. A novel detection model known as "wrist fracture detection-combo (WFD-C)" was created to improve these processes. The Huawei Turkey R&D Center supported the cooperative research project involving Gazi University, Medskor, and the center. Out of 26 models, the WFD-C model had the best detection result, averaging 0.8639 in precision. [12]

The research assessed how two deep convolutional neural networks (DCNNs) identified ankle fractures from radiographs. Using pre-trained Inception V3 and ResNet-50 models, the DCNNs were trained on 1,050 patients with fractures and healthy ankles. It was determined that 72 cases had hidden fractures that were not initially noticed. With 3-view images, the DCNNs performed better. The Inception V3 model, for example, achieved an impressive 98.7% sensitivity and 98.6% specificity with only one fracture missed. [13]

The research aimed to use deep learning to automatically find and classify hip fractures, cutting down on mistakes and speeding up surgery. It examined 1,118 studies' worth of hip and pelvic radiographs involving 3,026 hips that were bounding box-labeled and classified. Bounding box placement was automated by a Densely Connected Convolutional Neural Network (DenseNet), a deep learning-based object detection model. For fracture detection, the model showed a binary accuracy of 93.7%, sensitivity of 93.2%, and specificity of 94.2%. The accuracy in multiclass classification was 90.8%. [14]

Based on wrist X-rays, a research study devised a two-stage ensemble deep learning framework to autonomously differentiate between extra-articular and intra-articular distal radius fractures (DRFs). To simulate the search patterns of clinicians, an ensemble model of YOLOv5 networks was utilized in the first stage to identify the distal radius region of interest. In the second stage, fractures were classified into intra- and extra-articular categories using an ensemble model of EfficientNet-B3 networks. The framework showed encouraging results with an accuracy of 81%, an actual positive rate of 83%, a false positive rate of 27%, and an area under the receiver operating characteristic curve of 82%. [15]

Researchers used a dataset of 3,240 patients to compare deep learning for finding distal radius fractures (DRFs) with human diagnosis. Metrics like ROC curves, an area under the curve (AUC), accuracy, sensitivity, and specificity were used to assess the models' efficacy after they were developed using training and validation data in detecting DRFs. The deep learning ensemble model outperformed both orthopedic and radiology attending physicians in terms of accuracy (97.03%), sensitivity (95.70%), and specificity (98.37%). [16]

The research examined how deep learning models can find and rate the severity of lower-extremity fatigue fractures on plain X-rays. The ResNet-50 and triplet branch network models were built using 1,151 X-ray images from two clinical centers. The detection models showed high tibiofibular and foot sensitivity, specificity, and AUC in both internal testing and external validation sets. The diagnostic model's overall accuracy was remarkable for the foot (74.7% internal, 61.1% external) and tibiofibula (78.5% internal, 62.9% external). [17]

The research investigated the application of deep learning convolutional neural network (CNN) methodologies to material testing experiments to automate fracture identification. It considered the punch, shear, and uniaxial tensile tests, three typical material characterization tests. For surface crack identification, CNN architectures (ResNet, Inception, and VGG) were used; deeper architectures and filters with moderate sizes produced validation accuracies higher than 95%. Models based on CNN achieved validation accuracy levels higher than 99%. [18]

The study aimed to develop a deep neural network to improve fracture detection in emergency departments. To mimic the expertise of eighteen senior subspecialized orthopedic surgeons, the model was trained on a dataset of 135,409 radiographs. Unaided emergency medicine clinicians showed an average of 87.5% specificity and 80.8% sensitivity in a controlled experiment. The deep learning model helped to improve the sensitivity to 91.5%, specificity to 93.9%, and misinterpretation rate to 47.0%. [19]

Yadav and Rathor (February 2020) studied the difficulties in diagnosing bone fractures with X-ray imaging. To address overfitting problems, the authors used deep neural networks (DNNs) and data augmentation. Using 5-fold cross-validation, the study assessed the diagnostic accuracy of the proposed DNN model. The results showed an astounding 92.44% classification accuracy in identifying healthy from fractured bones, exceeding the accuracy rates reported for their model (86% and 84.7%, respectively). These results highlight the proposed DNN model's clinical potential for accurate bone fracture classification. [20]

2.3 Comparison between existing works

Table 2.1: Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Erzen et. al. [1]	YOLOv8	77.8%
2.	Sahin M. E. [2]	LDA	88.67%
3.	Inam, H. et al. [3]	SVM, Random Forest, CNN	SVM=98.29%
4.	Marwa, F. et. al.[4]	VGG-SegNet neural network	97.38%
5.	Tanzi, L. et al. [5]	CNN	94.5%
6.	Ouyang, C. H. et al. [6]	Xception convolutional neural network, CNN	Xception=91%
7.	Tanzi, L. et al. [7]	CNN	86%

Table 2.1: Comparative analysis with previous work

8.	Kong, S. H.et al. [8]	CNN	61.2%
9.	Chung,S.W.et al. [9]	CNN	96%
10.	Mutasa, S. et al. [10]	CNN, DNN	DNN=92.3%
11.	Olczak, J. et al. [11]	RestNet	——
12.	Hardalaç, F. et al. [12]	WFD-C	86.39%
13.	Ashkani-Esfahani, S. et. al. [13]	Inception V3, ResNet-50	Inception V3 = 98.7%
14.	Krogue, J. D. et. al. [14]	DenseNet	90.8%
15.	Min, H. et. al. [15]	YOLOv5, EfficientNet-B3 networks	EfficientNet-B3=81%
16.	Zhang, J. et. al. [16]	*Not Specified*	97.03%
17.	Wang, Y. et. al. [17]	ResNet-50	78.5%
18.	Karathanasopoulos, N. et. al. [18]	VGG, ResNet, Inception	——
19.	Lindsey, R. et. al. [19]	DNN	——
20.	Yadav, D. P et. al. [20]	DNN	92.44%

2.4 Open Issues

The problem investigated in this research, namely "Deep Learning-Based Advanced Image Processing for Bone Fracture Detection," is broad in its application to the field of medical diagnostics, especially in the area of orthopedics and bone health. Bone fractures, the commonest disease, require updated diagnosis methods, which have to be accurate and time efficient. The spectrum includes the bounds of the traditional methods of fracture detection, which quite often have problems related to sensitivity, specificity, and overall diagnostic accuracy. In addition, the study examines the use of transfer learning, a new idea in artificial intelligence, to enhance the performance of fracture detection systems. By means of transfer learning, the model is able to utilize the knowledge acquired despite the unrelated tasks which in this case is the complexities and variabilities of the X-ray images that depict bone fractures. It is deep Convolutional Neural Networks (CNNs) integration that makes the problem not only complex but really sophisticated. These models are very good in the extracting of the intricate patterns and features from the complex visual data, which makes them suitable for the tasks such as fracture detection within the medical images. Furthermore, the study of the problem scope includes not only that of the different approaches of detection and segmentation but also involves their analysis where the strengths, weaknesses and possible linkages of the approaches are examined. Analyzing the fracture-affected area revealing its spatial variations and characteristics is key for an accurate diagnosis. This research contribution is meant to be more advanced than the current detecting techniques. In other words, the nature of the problem includes the difficulties associated with bone fracture detection, the possibilities provided by transfer learning and deep CNNs, and the comparative evaluation of different methods. The aim of this study is to point out the nuances and perfect the existing diagnostic procedures so as to strengthen the public health system.

2.5 Summary

This study explores highlighting the role that deep Convolutional Neural Networks (CNNs) and transfer learning play in improving the precision and efficacy of fracture detection in medical X-ray images. Transfer learning enhances the model's fracture detection capability by utilizing information from unrelated tasks. The research examines a number of related studies that show how various deep learning models and methods work well in medical imaging. It draws attention to the advantages and disadvantages of the available techniques and suggests cutting-edge fixes to raise the precision and effectiveness of diagnosis. In order to improve public health outcomes, the research also investigates detection and segmentation techniques for better analysis of areas affected by fractures.

CHAPTER 3
METHODOLOGY

3.1 Overview

To increase the precision and effectiveness of fracture detection, CNN-based techniques are used in the "Deep Learning-Based Advanced Image Processing for Bone Fracture Detection" methodology. The effectiveness of the model is assessed using critical performance metrics like accuracy, precision, recall, and F1 score. Precision is the percentage of true positive predictions among all positive predictions; recall is the percentage of true positive cases that are correctly identified; accuracy evaluates the overall correctness of predictions; and the F1 score offers a balanced metric that combines recall and precision. In order to guarantee strong and trustworthy detection models, the methodology highlights how crucial it is to use these metrics.

3.2 Proposed Methodology/ System Design

Here, the proposed methodology for this study different machine learning detection model performance indices will be used as efficiency measurements markers of CNN based approaches.

Accuracy

Accuracy: Detection model accuracy is one metric. Accuracy is the model's predicted percentage. Accuracy is the percentage of properly classified pictures to total samples. Accuracy equation.

$$Accuracy=(TP+TN)/(TP+TN+FP+FN)$$

Precision:

Precision is the chance of a positive label and how many are positive. Precision shows how many accurately anticipated instances were positive. Precision is helpful when FP matters more than FN. Mathematically, it's this equation.:

$$Precision=TP/(TP+FP)$$

Recall:

Recall or Sensitivity measures how many positive expected occurrences were classified accurately. Recall is a helpful statistic when FN prevails over FP. F1-score is a further metric for detection accuracy that takes into account both recall and precision. Since precision and recall are harmonic means, the F1 score provides a comprehensive understanding of these two metrics. It reaches its optimum when Precision and Recall are equal. To figure it out, use the equation below:

Recall=TP/(TP+FN)

F-1 Score:

F1 score is a recall-precision metric of categorization accuracy. As F1-score is the harmonic mean of Precision and Recall, it gives a complete picture. Precision and Recall are optimal when equal. Equation.

F-1 Score=2*(Precision*Recall)/(Precision+Recall)

The percentage of people who do not have the ailment who have a negative test result is known as specificity. A highly specific test is effective in excluding the majority of individuals without the disease.

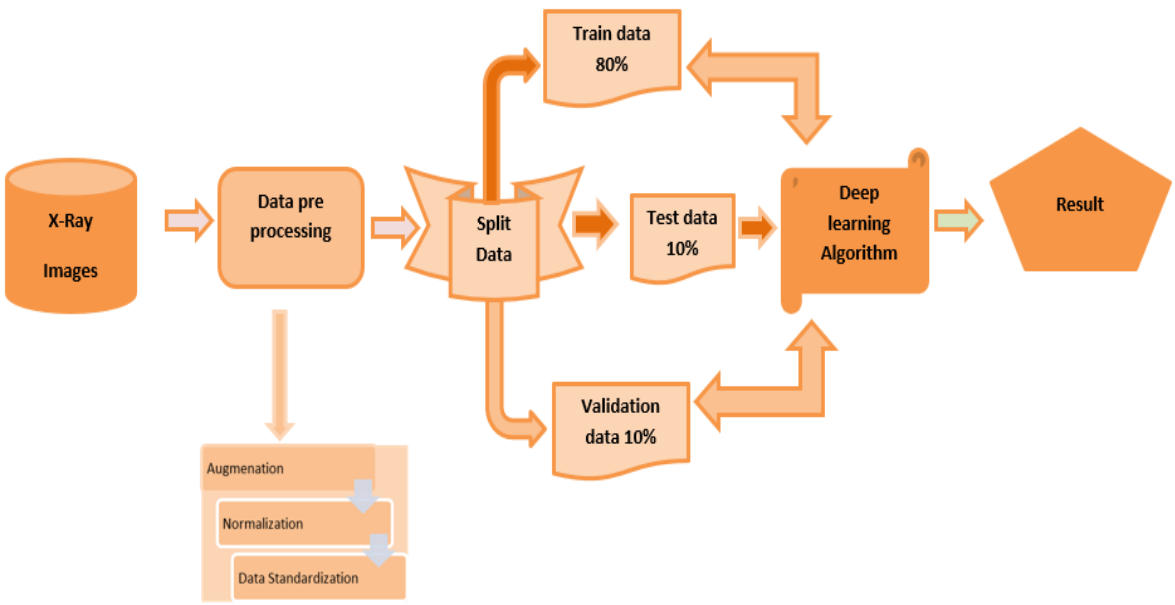

Figure 3.1: Proposed Methodology

3.3 Hardware/ Software Requirement

"Deep Learning-Based Advanced Image Processing for Bone Fracture Detection" is the title of the science undertaking that requires some unshakable requirements, which, in turn, would lead to its efficient implementation. These obligatory requirements consist of both hardware and software parts, together with data collection, model building, and verification.

Hardware Requirements

High-performance computing resources: Deep learning-based image processing is a sensorially demanding task that consumes a lot of processing power and memory, and availability of the computational infrastructure with enough processing power and memory is crucial in this regard.

Graphics Processing Unit (GPU)

GPU need to be available for the construction of the deep learning models, such as MobileNetV2, DenseNet201, Xception and Hybrid model (MobileNetV2 and Xception), by saved over 60 percent of training time.

Software Requirements

Deep learning frameworks: The well-known deep learning frameworks, such as TensorFlow or PyTorch, are implemented for the creation, training, and evaluation of the deep learning models.

Python programming language: Python is the programming language behind data analysis and deep learning.

Image processing libraries: Integration of libraries such as OpenCV for the preprocessing and augmentation of the medical images are going to translate to a better quality of the dataset which in return will enhance the robustness and quality of the model further.

Data Collection

Diverse and representative dataset: The next step is to have a complete dataset of bone images classified as being fractured or not fractured. This is a crucial step that should be followed so that the models that will be developed will be flexible and effective.

Annotated dataset: Regarding the necessity of using annotated data with obvious labels highlighting bone fractures for training and validation of deep learning models is unquestionable.

Model Development and Evaluation

Transfer learning models: Transfer learning method can be supported by utilizing pre-trained models e. g. MobileNet V2 and DenseNet201, which will be helpful in acquiring the existing knowledge endorsing the accuracy of the bone fracture detection.

Evaluation metrics: The correct evaluation metrics, which are accuracy, precision, recall and F1-score, should be predefined and used to evaluate the performance of deep learning models that are capable of identifying the bone fractures correctly.

3.4 Project Management and Financial Analysis

Project management and financial oversight are the key elements which contribute to the success and sustainability of the proposed research on this study. Project management is a process of meticulous planning, coordination, and execution of tasks, which includes from data collection to model development and deployment. To discuss a comprehensive project plan which will segment key milestones for productivity, resources will be allocated effectively and appropriately to implement set actions and produce this in accordance with the deadline.

Therefore, at the same time, robust financial management is going to be defining in terms of equipment acquisition, computational resources as well as collaborate research with collaborators in future. A clear and sensible financial management will be in place, which will guarantee that all financial resources are used in the best possible way without violating fiscal responsibility and accountability.

The applied strategies on the project management side as well as finance dimension provide the contemplation on the ground for the research team to get handle on the complexities of the study easily. Through coalescing resources with the research goals and establishing environments for collaboration and accountability, these strategies pave the smooth pathway for the research profile's and hence, add value to the bone fracture detection and healthcare technologies.

3.5 Summary

A significant amount of hardware and software are needed for this project, including GPU-based high-performance computing, deep learning frameworks like TensorFlow or PyTorch, and image processing libraries like OpenCV. For training and validation, a large, well-curated collection of annotated bone image images is necessary. To improve detection accuracy, transfer learning models such as MobileNetV2, DenseNet201, Xception and Hybrid model (MobileNetV2 and Xception) will be used. The success of the project depends on efficient resource allocation, financial oversight, and timeline and budget adherence. As a result of the integration of these tactics, healthcare technology will advance and accurate and dependable bone fracture detection models will be developed.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

The research on this study utilizes an advanced technical framework that combines cameras, Python programs, and databases. The hardware configuration necessitates a high-performance computing infrastructure, comprising robust CPUs, GPUs, sufficient memory, and abundant GPU bandwidth. Meanwhile, the software ecosystem relies on deep learning frameworks like TensorFlow or PyTorch, as well as image processing libraries such as OpenCV. Data preparation encompasses meticulous preprocessing, standardization, normalization, and annotation of X-ray images to guarantee consistency and precise labelling for training supervised models. The study utilizes transfer learning by leveraging pre-trained deep convolutional neural networks such as MobileNetV2, DenseNet201, Xception and Hybrid model (MobileNetV2 and Xception). This is followed by fine-tuning and hyperparameter optimization to improve the quality of detection and boost its capacity to generalize. Ethical issues mostly revolve around ensuring data privacy, safeguarding security, and gaining explicit informed agreement from people for the use of their photos.

4.2 Train Model

MobileNetV2: MobileNetV2 is a convolutional neural network that is optimized for low latency and energy consumption on devices such as mobile phones and embedded machines. Another reason for deploying deep neural networks on limited resources is their attempted solution using the compact bottleneck architecture with residual connections at bottleneck layers. In fact, the computing efficiency versus memory footprint trade-off is performed with more precision because the design concentrates on the main features extraction. In MobileNetV2 expansion layers between intermediate layers may use depth-wise convolutions in addition to filtering features and nonlinearity. The network of architecture starts with 32 filters from the first layer of the network, and then proceeds to a series of residual bottleneck layers. These processes include the transforming and creating of the initial features and then exploring more abstract representations staying with a deeper network. At the base of MobileNetV2 architecture can be defined the trade-off between the size of model and the performance, thus this architecture is good for real-time task like Bone fracture detection. The design of the algorithm results in the execution of inferences on mobile devices without degrading the accuracy level, which makes it possible to be deployed in the resource demanding applications at limited availability of resources.

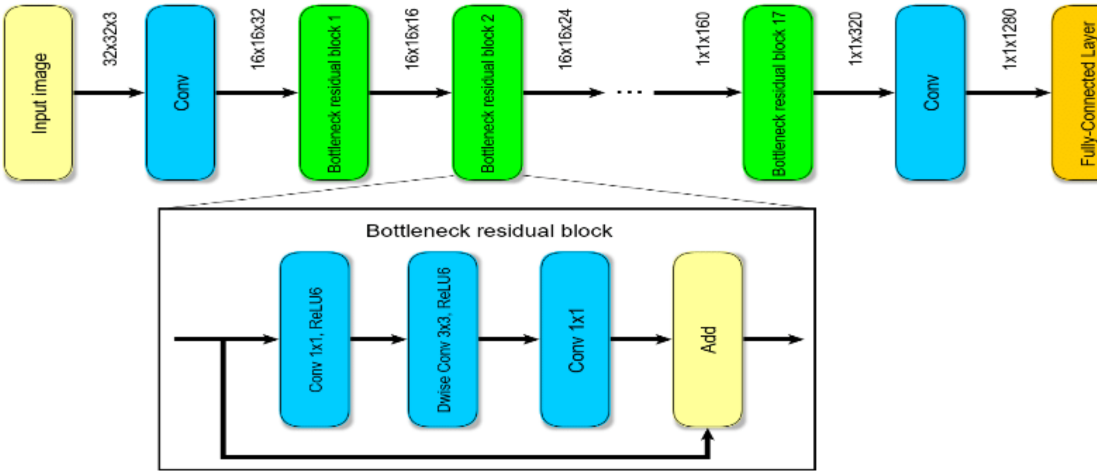

Figure 4.1: Schematic representation of MobileNetV2(Seidaliyeva et al.2020)

DenseNet201: which is a modification of the standard convolutional neural network structure is designed to improve depth and training effectiveness for deep learning models. Contrary to the usual architecture that only has limited connections between layers, DenseNet201 enables dense connections between the layers, which provides a channel for the direct information exchange between them. This connectivity structure is very dense hence features maps for each layer are received from all preceding layers through which feature reuse as well feature propagation throughout the network is allowed. Concatenation of features in DenseNet201 rather than summation results in the reduction of the required number of parameters along with featured reuse. It is this parameter-small design that makes DenseNet201 the best performer among the state-of-the-art on a variety of image detection tasks such as real-time determination of Bone Fracture. Its dense connectivity structure helps features to interact well and gradients to flow smoothly, such that resulting presentations are stronger and detection accuracy is increased.

To end with, one tangible obstacle that our team may encounter is the difficulty of using insufficient datasets for the deployment of each deep learning models. Here comes the transfer learning, which can be used to the advantage. It supplies us with the weights gained from pre-trained algorithms on datasets that are larger and independent of our case. In line with this, this strategy does not only ward off possible hypothetical decreased performances but then bolsters a myriad of increases, more so in situations where separation tasks are difficult and datasets for the trainings are fewer.

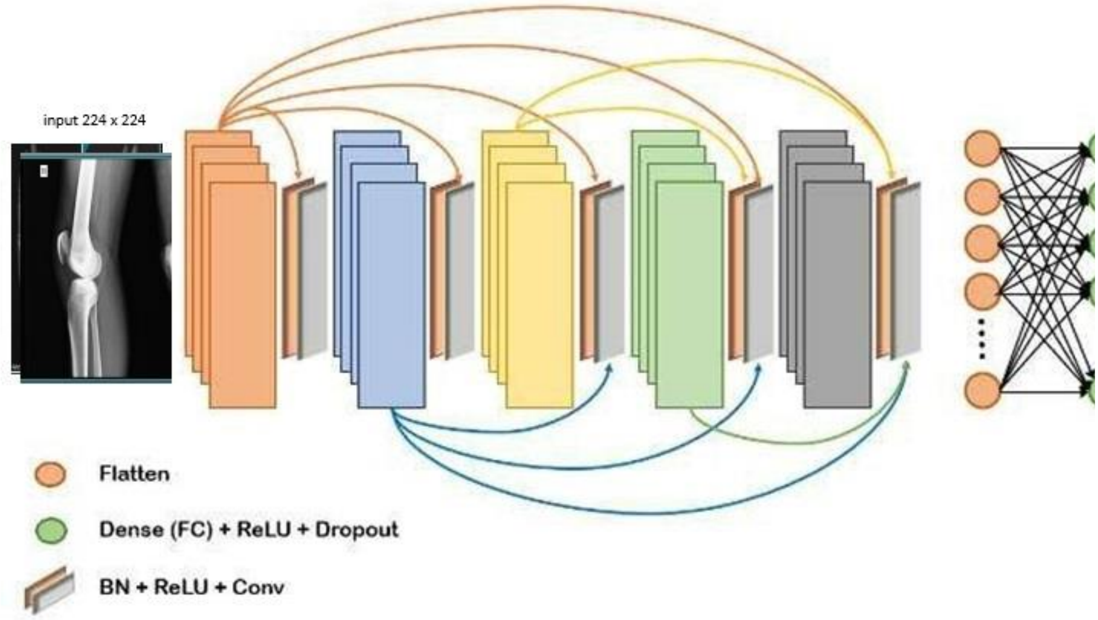

Figure 4.2: DenseNet201 Schematic Representation (Bilal et al. 2022)

Hybrid Model (MobileNetV2 and Xception): This model encompasses features from MobileNetV2 and Xception two of the robust deep convolutional neural networks over the dataset of ImageNet. The hybrid architecture starts by loading these models, but with their top layers frozen, thus applying only the convolutional base. This approach uses transfer learning, in which the pre-trained models are repurposed to predict the class of bone images into more than two classes.

As for the model construction, MobileNetV2 and Xception's output is average pooled to two dimensions and then concatenated into one feature vector. This concatenated feature vector is passed through a layer of batch normalization so as to stabilize and standardize the input. Dropout regularization is applied to prevent overfitting so as to increase generalization of the model. The dense layers come after, comprising a fully connected layer of 1024 neurons activated by ReLU that allows the model to learn increased complexity of the merged features. The final layer uses softmax activation to give the class probabilities as according to the number of classes in the training data. For training, model is compiled using Adam optimizer and categorical cross-entropy loss function, metrics to be optimized are accuracy. Both the training and the validation happen over a total number of 10 epochs, with the help of data generators that initialize and feed batches of images to the model, along with preprocessing them. Evaluations are made on the independent test set after training the model has been through to give results like accuracy and loss. The context of applying the hybrid model is validated by reasonable test accuracy attained for bone images and such a result show that the model is reliable for the purpose of classification. Lastly, the trained hybrid MobileNetV2-Xception model is saved so as to make its deployment and use in future possible for cognate applications like diagnoses or research relating to bone images. Feasibility and benefits of transfer learning and model fusion are also demonstrated in this work while emphasizing the use of pre-trained architectures for real-world image classification problem.

Transfer learning: Transfer learning, a technique that provides knowledge so acquired to be used in one domain to enrich learning in another, thus, is a major key of our methodology. In bone fracture detection through image detection, this approach may need to be used. It discards the last layers of a CNN that have already been trained and adds fresh new layers that are specifically taken for the task at hand. The first layers of deep learning process are task-specific. It is why transfer learning is a good way to improve detection performance. As the processing power and time are limited, the investigated CNN architectures are evaluated at different levels and finally, the most suitable model that best performs the transfer learning task in our case is applied. The adjustment of the network topology parameters and data set properties will be crucial in exploring the elements that promote the best performance of the detection within the scopes of our field. The training of a deep learning model with a small dataset is a complex task because it is prone to poor performance. Neyshabur et al. (2020) mention that transfer learning has the effect of eliminating "this hurdle" since it leverages the weights from the model trained on an unrelated and much larger dataset. This methodology in turn is responsible for the worthwhile results, especially with the complex segmentation tasks followed by small sample size target data set to use similar to the bone fracture detection task.
In short, transfer learning is a practical approach that trains a model with weights obtained from another, weider dataset of a larger size. These methodological breaks down open new ways of thinking, and generated from the performance improvements significantly, especially in situations when segmentation task is tough, or you do not have enough of the target training data.

4.3 System Testing

System testing for a deep learning-based image processing system for bone fracture diagnosis comprises many steps to guarantee the model's precision and dependability. The method starts with unit testing, whereby individual components such as picture preprocessing, model loading, and inference are evaluated in isolation to ensure accurate operation, identify code mistakes, evaluate edge cases, and assess robustness. Integration testing is conducted to verify the smooth collaboration of preprocessing, model inference, and post-processing phases, as well as to ensure the accurate flow of data through the system. Performance testing involves assessing the model's performance on a test set by measuring metrics like as accuracy, precision, recall, and F1 score. It also includes creating a confusion matrix to conduct a thorough investigation of the model's performance. Stress testing evaluates the performance of a system when subjected to a high workload and tests its capacity to handle larger amounts of data. Usability testing assesses the user interface for its intuitiveness and collects comments from healthcare experts. Security testing guarantees the confidentiality and safeguarding of patient data, as well as the prevention of vulnerabilities. Regression testing ensures that updates or modifications do not have a detrimental impact on current functionality and that consistency is maintained over time.

The study project's web application's product and how it works will now be looked at and analyzed.

Step-1:

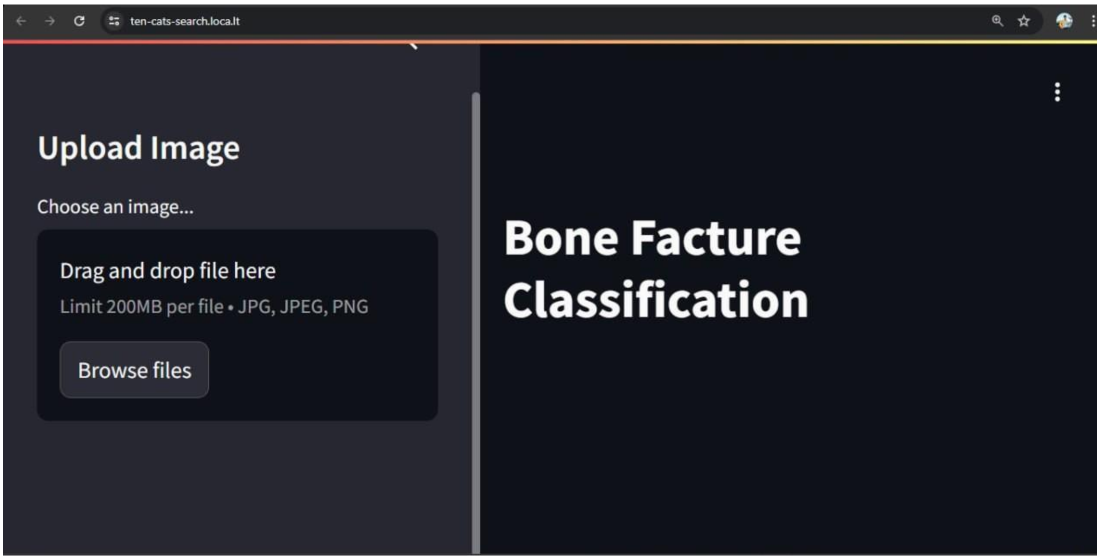

Figure 4.3: User interface of the web application

Step-2:

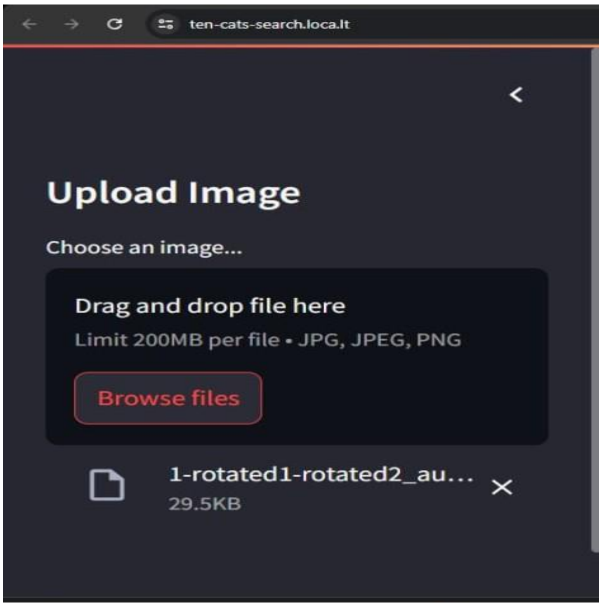

Figure 4.4: Uploading file

Step-3:

Figure 4.5: Output and result ‘Fractured’ and Not Fractured’

4.4 Summary

The study "Deep Learning Based Advanced Image Processing for Bone Fracture Detection" utilizes a complex technological framework that integrates cameras, Python programs, databases, and a web application. This framework necessitates strong hardware and powerful software. The hardware configuration comprises high-performance central processing units (CPUs), graphics processing units (GPUs), generous memory capacity, and adequate GPU bandwidth. The software ecosystem is built around deep learning frameworks like TensorFlow or PyTorch, as well as image processing libraries such as OpenCV. Data preparation encompasses meticulous preprocessing, standardization, normalization, and annotation of X-ray images to provide precise supervised training. The study utilizes transfer learning by employing pre-trained Convolutional Neural Networks (CNNs) such as MobileNetV2 and DenseNet201. This is followed by fine-tuning and hyperparameter optimization to improve the quality of detection. MobileNetV2 is designed to minimize the time delay and energy use, making it well-suited for jobs that need real-time processing. On the other hand, DenseNet201's dense networking enhances the propagation and reuse of features. The classification performance is further improved by merging MobileNetV2 and Xception in a hybrid model. Ethical issues mostly revolve around the protection of data privacy, ensuring robust security measures, and obtaining informed permission. Transfer learning is an important aspect of this methodology. It involves using models that have been trained on big datasets to enhance performance when dealing with restricted data. This approach proves to be feasible and beneficial for real-world applications. The online application incorporates these functionalities, enabling users to upload X-ray pictures for immediate identification of fractures, hence making the technology easily accessible and user-friendly for medical practitioners.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The advanced system of technological design that consists of the "camera," Python programs, and databases is the scientific approach that the " DEEP LEARNING BASED ADVANCE IMAGE PROCESSING FOR BONE FRACTURE DETECTION " research is completely based on.

Hardware Configuration

High-performance computing infrastructure: Not only the requirement of a powerful CPU and a GPU be obvious, but also the system should have sufficient amount of memory and bandwidth to the GPU.

Graphics Processing Unit (GPU)

GPU is applied for improving the training process as well as providing the necessary deep learning algorithm characteristics.

Software Environment

Deep learning frameworks: Implementing TensorFlow or PyTorch within the Python interface so to have them as the deep learning model development, training and evaluation tools.

Image processing libraries

The attribute that includes libraries like OpenCV for preprocessing and datasets like Bone X-ray images.

Data Preparation

Dataset preprocessing: via performing strict steps of data preprocessing, standardization, and normalization we can present homogeneity and objectivity in the input dataset.

Annotation: However, X-ray image could be tagged with the corresponding label namely as fracture, non-fracture which acts as a training data for the supervised learners.

Model Configuration

Transfer learning: This study uses the pre-trained Deep Convolutional Neural Network (CNN) architectures such as MobileNetV2, DenseNet201 for the detection of Bone fracture Usually, the process is fine-tuned afterward.

Hyperparameter tuning

The values of the model parameters should be fine-tuned as this has an overall significant impact on the quality of detection and its generalizability.

Ethical Considerations

Data privacy and security: Ensure that the data collected are used properly, in accordance with the ethical principles and rules to protect the privacy and the information security.

Informed consent: Once it is possible to get their approval, the images of those subject are going to be considered for incorporation in the data set.

5.2 Experimental/ Simulation Result

Result of Experiment 1: Original CNN

This section presents a comparative analysis of six original Convolutional Neural Network (CNN) architectures tailored for bone fracture detection: Because of this we are using MobileNetV2, DenseNet201, Xception and Hybrid model (MobileNetV2 and Xception). First, the accuracy of the model is the first objective being fulfilled and the only last step is the overall score or the generalization metrics. According to that, we talk about the description, the causal conditions, the markers that define the patching site, and the sites that need to be patched.

TABLE 5.1: Accuracy for detection of Individual CNN Networks in Detecting Bone Fracture

Architecture	**Training Accuracy**
MobileNetv2	97.27%
Dense Net 201	96.36%

TABLE 5.1: Accuracy for detection of Individual CNN Networks in Detecting Bone Fracture

Xception	98.63%
Hybrid (MobileNetv2 & Xception)	99.04%

Lastly, the topmost model was provided by Hybrid with the accuracy score of 99 percent, which means that they were less mistaken. 69% of the x-ray. Those that are on camera, that is, 99% of them are getting good in their actions. That other approach, however, was more accurate with the performance on the test dataset being of 99. 99%. 69% recall. 95. They mention the ten percent, but don't even bother to compare it to cars that are driven in the road. In my opinion, they are like day and night. The cognitive ability of the doctor who is responsible for operating the imaging machine for fracture is very important to the diagnosis; so, the quality of the diagnosis is very important. the site uses the accuracy as shows in table 5.1 Yet the peak moment of Martin Luther King speech has usurped in me another image I cannot hardly compare to any other one – I'm sure. The initial stage may be the first step of the selection model that will present the hypothetical pros and cons of traditional models followed by the introduction of deep learning methods as a tool in the field of medical imaging analysis.

TABLE 5.2: Precision, Recall, F1-Score, and Support (n) for original CNN networks (depending on the number of pictures, n=numbers), including Mobile Net V2

Mobile Net V2	**Precision**	**Recall**	**F1-Score**	**Support**
Fractured	0.95	1.00	0.97	1000
Not-fractured	1.00	0.94	0.97	1000
Accuracy			0.97	2000
Macro Avg	0.97	0.97	0.97	2000
Weighted Avg	0.97	0.97	0.97	2000

TABLE 5.3: Precision, Recall, F1-Score, and Support (n) for original CNN networks (depending on the number of pictures, n=numbers), including Dense Net201

Dense Net201	Precision	Recall	F1-Score	Support
Fractured	0.96	0.97	0.96	1000
Not-fractured	0.97	0.95	0.96	1000
Accuracy			0.96	2000
Macro Avg	0.96	0.96	0.96	2000
Weighted Avg	0.96	0.96	0.96	2000

TABLE 5.4: Precision, Recall, F1-Score, and Support (n) for original CNN networks (depending on the number of pictures, n=numbers), including Xception

Xception	Precision	Recall	F1-Score	Support
Fractured	0.98	1.00	0.99	1000
Not-fractured	1.00	0.98	0.99	1000
Accuracy			0.99	2000
Macro Avg	0.99	0.99	0.99	2000
Weighted Avg	0.99	0.99	0.99	2000

TABLE 5.5: Precision, Recall, F1-Score, and Support (n) for original CNN networks (depending on the number of pictures, n=numbers), including Hybrid Model

Hybrid (Mobile Net V2 & Xception)	Precision	Recall	F1-Score	Support
Fractured	0.99	0.99	0.99	1000
Not-fractured	0.99	0.99	0.99	1000
Accuracy			0.99	2000
Macro Avg	0.99	0.99	0.99	2000
Weighted Avg	0.99	0.99	0.99	2000

Training and Validation Accuracy and loss of Original CNN Networks: Represents the training and validation accuracy of the initial model, with the number of epochs on the x-axis and the accuracy and loss percentages on the y-axis. In the figure, training and validation data are adequately divided, and there is no overfitting.

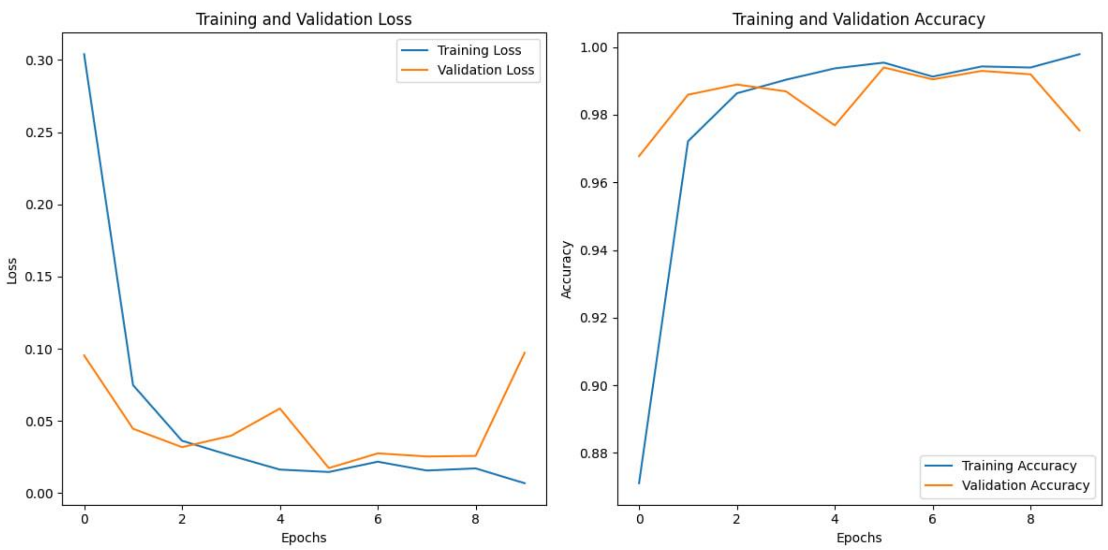

Figure 5.1: Training and validation accuracy and loss over the epoch (Mobile Net V2)

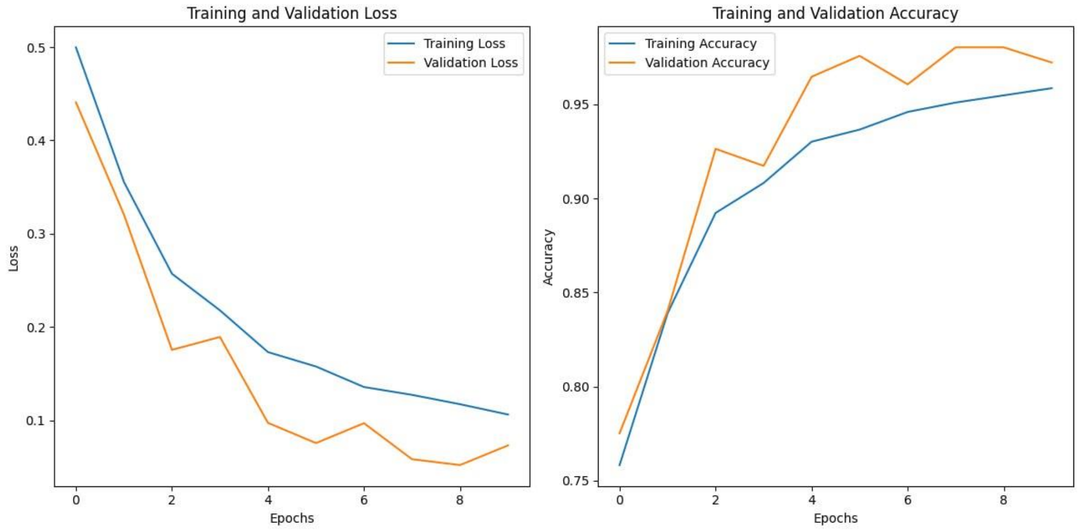

Figure 5.2: Training and validation accuracy and loss over the epochs (Dense Net 201)

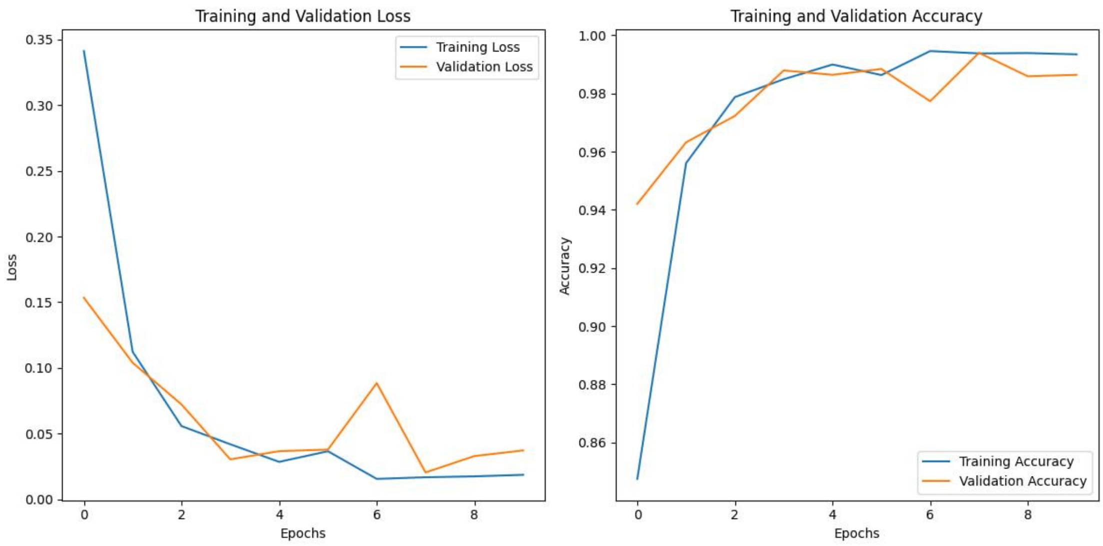

Figure 5.3: Training and validation accuracy and loss over the epochs (Xception)

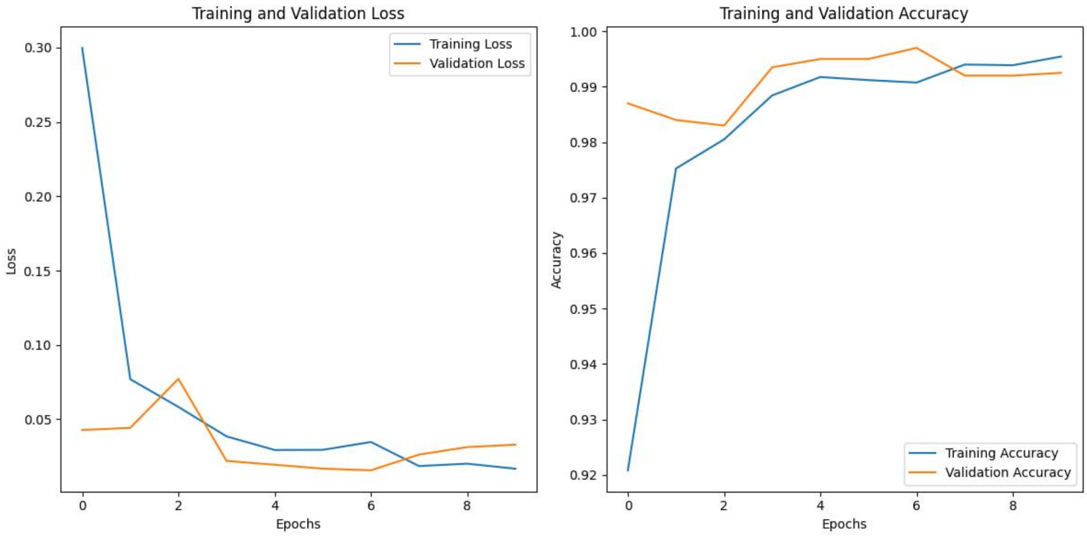

Figure 5.4: Training and validation accuracy and loss over the epochs (MobileNetV2 and Xception)

Confusion Matrix after Original CNN:

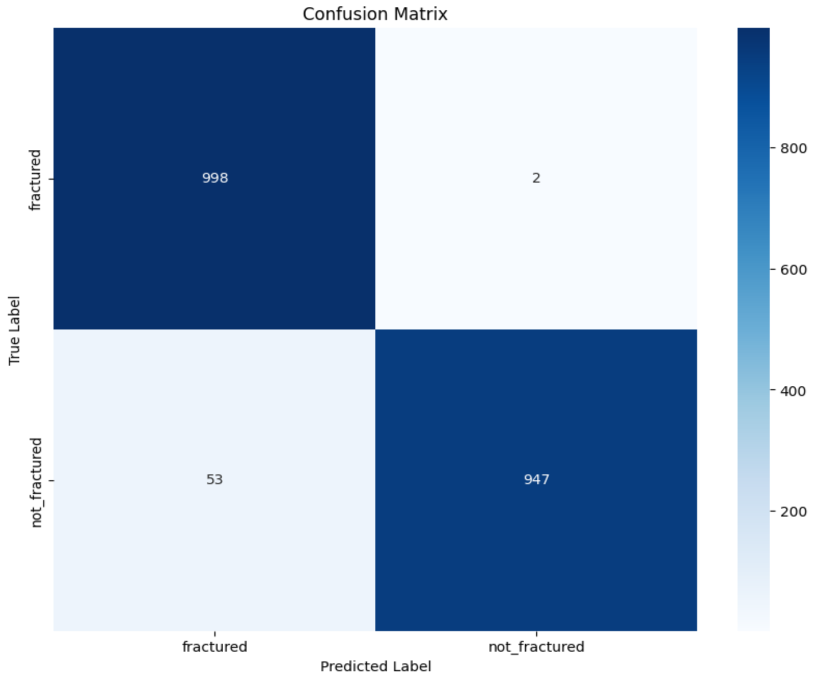

Figure 5.5: CM after Original Mobile Net V2

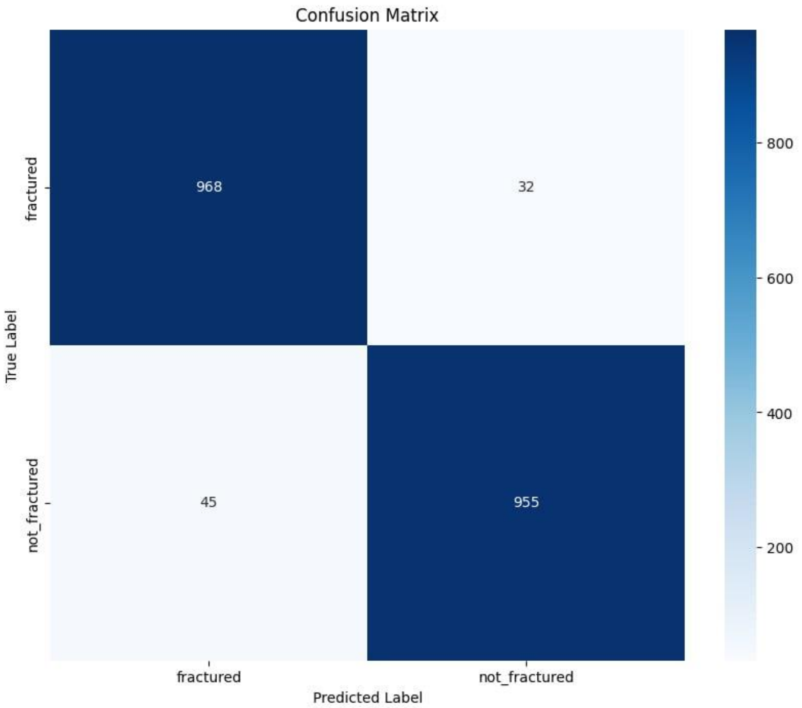

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Figure 5.6: CM after Original Dense Net 201.

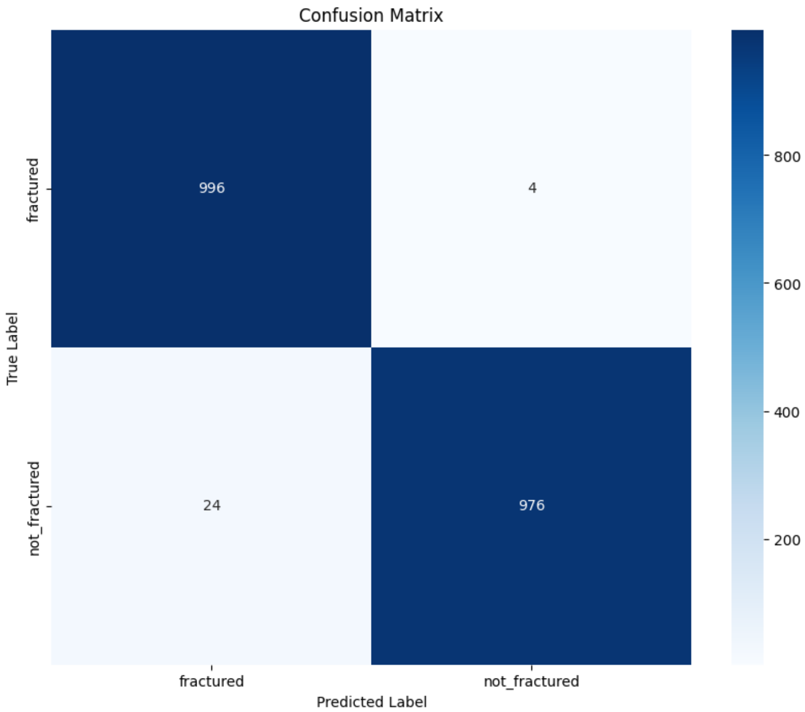

Figure 5.7: CM after Original Xception.

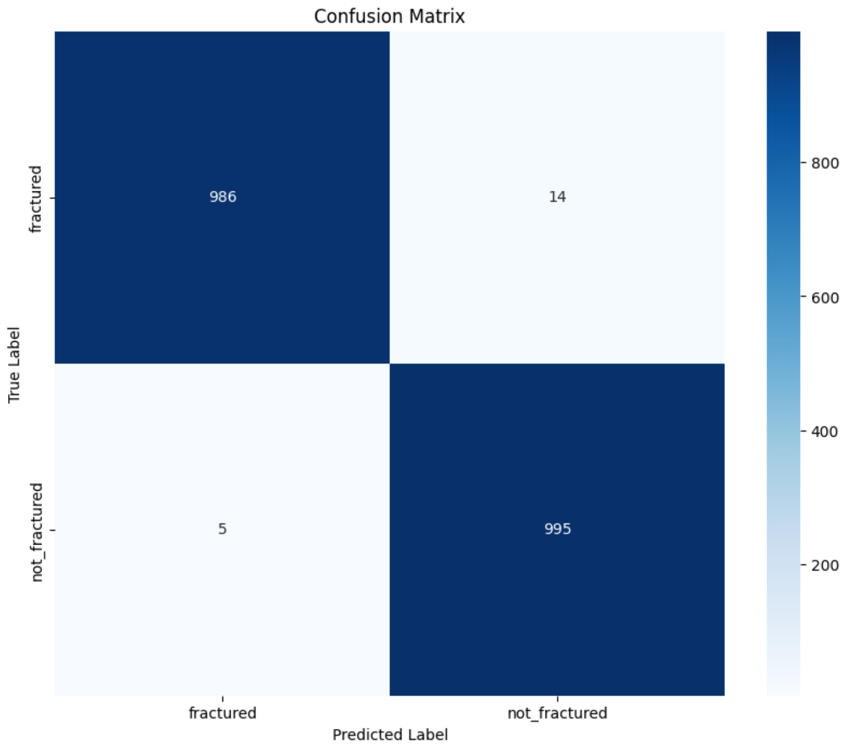

Figure 5.8: CM after Original MobileNetV2 and Xception.

Result of Experiment 2: Transfer Learning

A contrast is made between 4 different original Convolutional Neural Networks (CNNs) that are adopted, so that the best performing architecture can be selected. In the analysis, the researcher examines the detection performance based on several aspects such as the network architecture as well as how they are applied in the bone fracture detection task. Four different convolutional neural network models have been checked which are MobileNetV2, DenseNet201, Xception and Hybrid model (MobileNetV2 and Xception). These models are considered to be a great option for medical image analysis related tasks.

The following section presents an analysis of the metrics that were used to evaluate this model and the main performance indicators that were taken into account for these models, that is, the accuracy, precision, recall, and F1 score. Besides the measurable figures, the current work also addresses the quality dimensions like model workability, their behavior under different trialing environments and finally, also addresses the diagnosis of bone fractures.

This section also explores some of the possible reasons for the variances in results, e. g. architecture of the Convolutional Neural Networks (CNNs), setting of parameters, and the ability of those CNNs to address the particularities of imaging of bone fractures. This concept specifically deals with the quality and content of the research in terms of the provision of solutions beyond the figures and statistics while also including the model performance from the quantitative and qualitative points of view. The discussion would also be augmented by pinpointing the areas that need improvement taking both models into consideration; thus, be able to give valuable hints for the updates to implement these two models to increase their efficiency in detecting bone fractures. This involves a thorough examination of those parts of the models that perform the worst. Improvements in the model architecture, the training techniques or the datasets augmentation methods can be done on the basis of this examination. Simply put, this part of the paper not only presents the quantitative and qualitative review but also brings you to the understanding of the inner mechanism of the MobileNetV2 and DenseNet201 that is responsible for their detection behaviors in the subject of bone fracture detection.

TABLE 5.6: Accuracy for detection of Individual CNN Networks in Detecting Bone fracture

Architecture	**Testing Accuracy**
MobileNetv2	97.27%
DenseNet201	96.36%
Xception	98.63%
Hybrid (MobileNetv2 & Xception)	99.04%

5.3 Performance/ Comparative Analysis

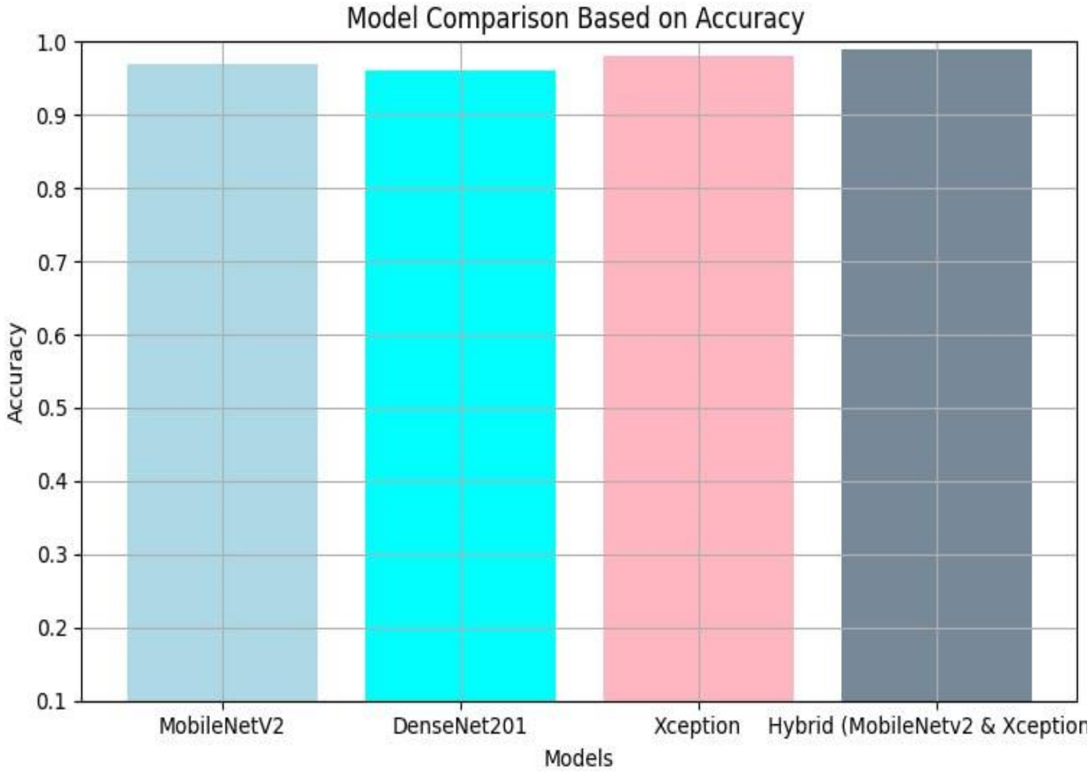

Figure 5.9: Accuracy comparison among individual Mobile Net V2, Dense Net 201, Xception and Hybrid model

This comprehensive study delves into the efficacy of deep convolutional neural networks (CNNs) in recognizing and segmenting two distinct types of Bone x-ray images. Leveraging a substantial dataset of 4623 original photos, the research employs a sophisticated augmentation approach, generating eleven images from a single photograph. In the realm of chest X-ray detection, the study explores the utility of original CNNs, transfer learning techniques, and ensemble models. Notably, the investigation scrutinizes the computation of detection and segmentation, recognizing these as distinct processes within the diagnostic pipeline. MobileNetV2 and Xception emerge as front-runners, achieving an impressive accuracy score of 99%, as visually depicted in Figure 5.9. The research sheds light on the nuanced impacts of transfer learning, revealing that accuracy diminishes when the input picture deviates from the training data in the ImageNet Dataset. Intriguingly, variations in background noise and the utilization of diverse augmentation strategies independently with test sets are identified as potential factors contributing to decreased performance.

In-depth analysis indicates that the original CNN model, when trained and evaluated using comparable input, exhibits enhanced predictive capabilities for unknown data. Nevertheless, the study recognizes limitations in dataset size, highlighting the potential impact on prediction capabilities, especially in the context of transfer learning. Insights from previous research reinforce the suggestion to increase dataset size, particularly when the input picture undergoes augmentation updates. The study underscores the potential superiority of ensemble models over individual CNN architectures, emphasizing that an ensemble of multiple models may outperform a single model, even if a specific CNN architecture exhibits suboptimal performance.

5.4 Summary

This research investigates the utilization of sophisticated deep learning methods to identify bone fractures in X-ray pictures. The study specifically emphasizes the combination of powerful hardware, deep learning frameworks like TensorFlow and PyTorch, and image processing tools such as OpenCV. The text emphasizes the significance of transfer learning and the utilization of pre-trained CNN models such as MobileNetV2, DenseNet201, Xception and Hybrid to enhance diagnostic precision. The experimental findings demonstrate that Hybrid model obtained an exceptional training accuracy of 99.04%, whereas MobileNetV2, DenseNet201 and Xception achieved a lower accuracy of 97.27%, 96.36% and 98.63%. The paper also investigates the influence of other parameters on model performance, including dataset size, augmentation strategies, and the advantages of ensemble models. The emphasis is placed on ethical aspects, such as data protection and informed permission. The research indicates that ensemble models may have better prediction capacities than individual CNN designs. This suggests that additional enhancements in training methodologies and dataset augmentation are needed to increase the effectiveness of bone fracture detection systems.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The study "A deep learning method is applied to bone fracture detection based upon advanced image processing" could revolutionize medical diagnostics and society. Advanced AI technologies can detect bone fractures accurately and quickly, improving patient outcomes and society. The global healthcare crisis of bone fractures from traffic accidents, falls, and sports injuries is addressed by this innovation. With transfer learning and deep CNNs, the study improves diagnostic accuracy, giving doctors reliable insights for patient care. Simplifying diagnostic processes, reducing misdiagnoses, and speeding treatment interventions improves patient care quality. Multiple models are combined to create a widely applicable diagnostic tool, especially in countries with limited medical access. This method democratizes advanced healthcare technologies to close health gaps and provide quality care to underserved areas, improving lives worldwide.

6.2 Impact on Society & Environment

This research study, "A deep learning method is applied to bone fracture detection based upon advanced image processing" is full of social and health implications. In addition to being academically rewarding, it can definitely be a tool to invest in communities and impart them with the knowledge to change their lives. The study is going to revolutionize medical diagnostics by using the precise and timely detection of bone fractures using advanced artificial intelligence technologies, which will, in turn, lead to better patient outcomes and wider societal benefits. Fractures of the bone, proved in road traffic accident, by falling from height, and sports related injuries are massive problem of the health-care system reaching all the countries. The basis of our research is utilization of transfer learning in tandem with the deep CNNs for enhancing accuracy and the rate of fracture identification; as such, doctors will rely on informed insights to make well-determined decisions about patient diagnosis and treatment. The social impact of this research is in the area of public health where the diagnostic processes are simplified thus the number of misdiagnoses is reduced, the treatment interventions are faster and hence the patient care is improved. The blend of the multiple models, including the computational one, as well as the comparison study section of our research, is meant to develop the diagnostic model that can be easily and successfully applicable in healthcare with less invasion of patients' lives in different countries of the world. What's more, using sophisticated and affordable fracture detecting products saves money while its simplicity leverages on this to reach the small and remote areas where medical services maybe inaccessible. The democratization of the most up-to-date healthcare technologies is the way to the global health projects which are focused on the decrease of the health gaps and the increase of overall healthcare equity.

6.3 Ethical Aspects

Ethical considerations pervade every feature of the entire research process. The research put first the privacy and confidentiality of the patients and make sure that the use of medical images is in line with the ethical guidelines and the regulatory standards. Informed consent being taken whenever necessary and the process of the research being transparent provides for an appropriate knowledge dissemination process. Taking care to ensure ethically responsible implementation is our promise to serve the welfare of society and technology in healthcare in the most responsible fashion.

6.4 Sustainability Plan

Our sustainability plan is aimed at reducing the environmental footprint and at the same time preserving the positive social effects. The research strongly believes in computational efficiency, energy efficient algorithms, as well as green data management. A continuous monitoring and amendments to the sustainable procedures in line with our promise of the sustainable and environmental-friendly scientific innovation is our ongoing process.

6.5 Summary

The research study "A deep learning method is applied to bone fracture detection based upon advanced image processing" claims to revolutionize medical diagnostics with cutting-edge AI technology, with substantial social and health benefits. By increasing diagnostic precision and optimizing patient care, this breakthrough tackles worldwide healthcare issues associated with bone fractures from falls, accidents, and sports-related injuries. The study has a significant impact on society by streamlining diagnostic procedures, decreasing false positives, and providing high-quality care to underprivileged communities. While a sustainability plan focuses on lowering environmental effect through energy-efficient algorithms and green data management, ethical concerns guarantee patient privacy and informed consent. This work advances sustainable scientific innovation, global health equity, and the democratization of healthcare technologies.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

From the survey, it has been realized that a correct and quick diagnosis of a fracture is among the clinical practices that need to be evidence based. The experiment with the efficacy of deep CNN has remarkable results especially in the case of segmentation techniques, which improved the precision, including small datasets. The other important result of the study is that the stack composed of Hybrid (ensembles) has a higher accuracy than the individual models, which makes it possible to use such ensembles in fracture diagnosis. On the one hand, our work shows a way how the problem could be dealt with, but, at the same time, it opens up new issues to be explored. Where ensemble approach provides more accurate results, the misjudgment scenarios necessitate a thorough investigation into other image-processing methods. Investigations as tracer-particle ensemble method can be one of the ways but this has computational limitations.

7.2 Further Suggested Works

The prospect of the application of the deep learning algorithms in the area of bone fracture detection should not be undermined. Our study is the first part of the process of finding other image-processing methods solving the inaccuracies of the ensemble methods. The integration of segmentation techniques at the first stage before is a way where you combine the feature extraction capabilities and improve the model performance as a whole. Emphasizing the necessity of future studies for creating relevant ensemble techniques and performing medical application's studies for the deep learning approach may be useful for providing unambiguous evidence of the deep learning approach in diagnosing fracture. By means of expanding the research area and introduction of new technologies the area of medical image analysis can be highly developed and, as a result, it will be able to improve the prognosis of the patients with the fractures.

7.3 Limitations/ Conflict of Interests

This study on deep learning-based enhanced image processing for bone fracture diagnosis has potential, however it has limitations and potential conflicts of interest. First, training data quality and diversity are crucial to deep learning models like MobileNetV2, DenseNet201, Xception and Hybrid model. Dataset biases or insufficiencies may impair model performance and clinical applicability. These models demand a lot of computational resources to train and evaluate, which may be difficult in resource-constrained healthcare settings. The study emphasizes ethical considerations and patient confidentiality, but ethical norms must be monitored and updated as technology change. Conflict of interest declarations include researchers linked with organizations or companies that may have a stake in the research's results, influencing interpretations or recommendations. Transparency in reporting methods and results reduces these concerns but requires constant monitoring. Addressing these constraints and conflicts of interest is crucial to the credibility, usefulness, and ethical integrity of this research in improving bone fracture diagnosis.

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APPENDIX A

Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Analysis

Title: Deep Learning Based Advance Image Processing for Bone Fracture Detection

Students ID: 203-15-14511, 203-15-14512

CO Description for FYDP-Phase-I

CO	CO Descriptions	PO
CO1	Integrate recently gained and previously acquired knowledge to identify a real-life complex engineering problem for the Final Year Design Project	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for the Final Year Design Project	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish the goals for the Final Year Design Project	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the Final Year Design Project	**PO11**

Addressing of COs, Knowledge Profile (K), and Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attain ment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, and CO3	The "Deep Learning Based Advance Image Processing for Bone Fracture Detection" project showcases the integration of specialized knowledge and engineering fundamentals to create a novel approach to automated fracture detection. Our goal is to increase the efficiency and accuracy of orthopedic diagnosis by utilizing machine learning models and sophisticated image processing techniques.	**Page no: iv**

				All things considered, our project complies with engineering and professional standards while integrating multiple components. Our goal is to provide a complete automated bone fracture detection solution that satisfies healthcare providers' demands and improves patient care by fusing cutting-edge image processing methods with an intuitive web-based interface.	**Page no: 3-5**
				Our project's foundation was established by our research into previous models that had comparable objectives. This research informed our design choices, directed our methodology, and provided a framework for assessing and contrasting our suggested solution.	**Page no: 11-12**
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2	The goal of our study was to use deep learning-based image processing techniques to enhance the field of bone fracture diagnosis, we ran into issues with regulatory compliance, diversity, and dataset availability.	**Page no: 2-3**
3.	**EP3: Depth of analysis required**	Yes	CO2	Our goal is to ensure that our deep learning-based image processing system could reliably and efficiently identify bone fractures in medical images by choosing the best algorithm based on empirical data and experimental validation. We aimed to address the issues raised by the quantity and variety of available possibilities by carefully assessing and selecting the method, expanding the field of bone fracture detection through cutting-edge computational approaches.	**Page no: 2**

4.	**EP4: Familiarity of Issues**	Yes	CO3	Through a thorough comprehension of these ideas and approaches, we wanted to provide a solid testing ground for our fracture detection system. With the use of this framework, we would be able to evaluate our system's efficacy and accuracy objectively, confirming its value and dependability in clinical settings.	**Page no: 18-24**
5.	**EP5: Extends of stakeholders involved and conflicting requirements**	Yes	CO3	We sought to create a solid evaluation framework for our fracture detection algorithm by obtaining a thorough understanding of these ideas and techniques. Our system's usefulness and dependability in clinical practice would be validated by our ability to test its correctness and efficacy objectively with this framework.	**Page no: 14-17**
6.	**EP6: Interdependence**	Yes	CO3	We guarantee a methodical and effective approach to creating and implementing our deep learning-based bone fracture detection system by organizing our project into three interconnected subsystems. Every subsystem is essential to the overall workflow because it enhances the final product's dependability and efficacy.	**Page no: 18 - 24**
7.	**EP7: Cost analysis**	Yes	CO4	We have prepared a budget to evaluate and estimate the cost required for our FYDP.	**Page no: 17**

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