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Classification of Fractured Bones using Machine Learning

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ABSTRACT— Rapid advancements in technology have significantly influenced various domains, particularly the medical field, where innovative approaches are enhancing diagnostic and therapeutic procedures. Despite these developments, conventional techniques such as X-ray imaging remain indispensable due to their reliability, cost-effectiveness, and widespread availability. X-ray imaging is extensively utilized for the detection of bone fractures; however, certain fractures may be subtle or situated in anatomically complex regions, thereby increasing the likelihood of misdiagnosis. To address these challenges, this study proposes an intelligent automated system for the detection and classification of bone fractures using advanced computational methods. The proposed framework consists of two primary stages: initially, X-ray images are subjected to preprocessing techniques, including noise reduction, contrast enhancement, edge detection, and segmentation, to improve image quality and extract relevant structural features; subsequently, a backpropagation neural network is employed for classification, wherein the model is trained on processed images to learn discriminative features of various fracture types and evaluated on unseen data to assess its performance. Experimental results demonstrate that the proposed system achieves high levels of accuracy and efficiency, indicating that the integration of image processing techniques with neural network-based classification can significantly improve fracture detection and assist healthcare professionals in making more precise and timely clinical decisions.

INTRODUCTION

In human body, there are total 206 types of different bones. Each bone has its own importance. It is very important to correctly identify human bone and then suggest treatment. To classify the human bones, we will use Musculoskeletal Radiographs (MURA) dataset. MURA dataset is one of the largest public radiographic image datasets. MURA dataset contains total 40,005 x-ray images of 14,052 patients, in which 36,808 images use as a training set and rest 3197 images use the testing set. These all images belong to seven different categories of bones such as finger, elbow, hand, forearm, humerus, wrist and shoulder**.**A machine can be learned in two different ways either as supervised learning or unsupervised learning. In supervised learning, already we have some labeled data through which we train our machine and perform classification/prediction based on training . In unsupervised learning, we have unlabeled data. In our case, we used supervised learning to train our machine. Classification is a concept of supervised machine learning in which the computer learns from the labeled data we input and then uses this learning to classify new data given to it. Classification is used to predict the category of data we provide. For the classification of human bones, we require some x-ray images of the different body part. For that region, we used Musculoskeletal Radiographs (MURA) dataset. This MURA dataset contains seven different categories of human bones belonging to Elbow, Hand, Wrist, Shoulder, Finger, Humorous and Forearm. Each category of bone has some x-ray images with respect to the number of patients.

I. PROBLEM DEFINITION

Accurate detection and classification of bone fractures using X-ray imaging remain a significant challenge in medical diagnostics, particularly when fractures are subtle, minimally displaced, or located in anatomically complex regions. Traditional manual interpretation of X-ray images relies heavily on the expertise of radiologists and clinicians, which may lead to variability in diagnosis, increased workload, and potential misclassification or oversight of fractures. These limitations can result in delayed treatment and adverse clinical outcomes. Therefore, there is a critical need for an efficient, reliable, and automated system that can assist in identifying and classifying bone fractures with high accuracy. The problem addressed in this study is the development of an intelligent framework that leverages image processing techniques for feature extraction and a backpropagation neural network for robust classification of fracture types, thereby improving diagnostic precision and supporting clinical decision-making.

1.2 PROJECT FEATURES

The proposed system provides a simple and efficient interface for uploading and analyzing bone X-ray images. It performs preprocessing and feature extraction by converting images into pixel intensity values, ensuring consistency and improved image quality. The dataset is automatically divided into training and testing sets, reducing manual effort and errors. A Random Forest model is then trained on the processed data to classify different bone types based on learned features, achieving high prediction accuracy. Additionally, the system supports real-time classification by allowing users to upload new test images. It accurately identifies bone types such as wrist, finger, and elbow, and displays results directly on the image for easy interpretation. The user-friendly graphical interface ensures ease of use, while automation reduces time and effort for healthcare professionals. The system is also scalable, enabling further improvement with larger datasets, making it a reliable and adaptable solution for medical diagnosis support.

Related Work

Many researchers have proposed machine learning approaches for detecting cyber attacks and insider threats. One research study proposed a phishing email detection system using machine learning algorithms such as Support Vector Machine (SVM), Naïve Bayes, and Long Short Term Memory (LSTM). The system analyzed email content and classified messages as phishing or legitimate. Another study focused on detecting insider threats by analyzing user behavior patterns in enterprise networks. The researchers used anomaly detection techniques to identify suspicious user activities. Some researchers have developed machine learning frameworks that analyze system logs and user access records to detect abnormal patterns that indicate malicious activities. Although these methods provide good detection accuracy, there is still a need for improved systems that can efficiently analyze large datasets and detect privilege escalation attacks in cloud environments.

II. METHODOLOGY

The proposed system for bone fracture classification follows a structured machine learning–based methodology consisting of multiple stages, including data acquisition, preprocessing, feature extraction, model training, and classification.

1. Data Collection

The data used in this study is obtained from the publicly available **MURA (Musculoskeletal Radiographs) dataset**, which is one of the largest datasets for bone X-ray analysis. It consists of approximately 40,000 X-ray images collected from over 14,000 patients, covering multiple types of bones such as finger, wrist, elbow, shoulder, hand, forearm, and humerus.

2. Data Preprocessing

The collected X-ray dataset is preprocessed to improve image quality and consistency. The steps include:

- Image resizing to a uniform size
- Noise reduction to remove distortions
- Image enhancement (contrast improvement)
- Feature extraction (conversion to pixel intensity values)
- Normalization of pixel values

After preprocessing, the dataset is split into:

- **Training data (80%)**
- **Testing data (20%)**

3. Model Training

Machine learning algorithms are applied to train the system, including:

- Random Forest
- Convolutional Neural Network (CNN)
- Backpropagation Neural Network (BPNN)

Each model is trained using the training dataset to learn patterns and features of different bone types from X-ray images.

4. Model Evaluation

The performance of each model is evaluated using the following metrics:

- Accuracy
- Precision
- Recall
- F1-score

A confusion matrix is also used to analyze correct and incorrect classifications of bone types.

5. Result Comparison

Random Forest achieved the best performance with high accuracy (~84%) and stable results, making it the most suitable model for this system. CNN provided higher accuracy but required more computational resources and training time. BPNN showed moderate performance but needed careful tuning, making it less efficient compared to Random Forest.

6.Prediction

The trained model is used to predict the class of new X-ray images by analyzing extracted features. When a test image is uploaded, the system processes it and applies the Random Forest model to classify the bone type. The predicted result is displayed on the image, helping in identifying the bone and possible fracture location.

7. Output Generation

Finally, the system provides: Prediction results , Graphical analysis , Performance comparison . This helps administrators take necessary actions to improve cloud security..

III. PROPOSED SYSTEM

IV. Proposed System

The proposed system is designed to automatically detect and classify bone types from X-ray images using machine learning techniques.
It uses the MURA dataset, which contains labeled X-ray images of different bones.
The system begins by preprocessing images to improve quality and consistency.
Feature extraction is performed by converting images

into pixel intensity values.
The dataset is then split into training (80%) and testing (20%) sets.
A Random Forest algorithm is used to train the model on extracted features.
The trained model learns patterns of different bone structures.
The system can classify bone types such as wrist, finger, elbow, and others.
It allows users to upload new X-ray images for real-time prediction.
The system improves accuracy, reduces manual effort, and supports doctors in diagnosis.

V. IMPLEMENTATION DETAILS

The implementation phase focuses on transforming the system design into a fully functional application. It involves developing modules such as dataset upload, feature extraction, model training, and prediction. The system is implemented using Python with libraries like NumPy, OpenCV, and Scikit-learn. Proper user guidance is provided through a simple and interactive graphical user interface (GUI), allowing users to easily perform operations such as uploading datasets, training the model, and testing new images. The system requires minimal training for users, as the interface is intuitive and easy to understand. All processes, including data preprocessing, feature extraction, and classification, are automated to reduce manual effort and human errors. The results are displayed clearly on the screen, making interpretation simple

4.1 ALGORITHMS USED

4.1.1 RANDOM FOREST

Random Forest is a supervised machine learning algorithm used for classification tasks. It works by creating multiple decision trees during training and combining their outputs to improve prediction accuracy. Each tree is trained on a random subset of data and features, which helps reduce overfitting and enhances model performance. In this project, Random Forest is used to classify bone types from X-ray images based on extracted pixel features. It provides high accuracy, handles large datasets efficiently, and delivers stable results, making it the primary algorithm used in the system.

4.1.2 CONVOLUTIONAL NEURAL NETWORK (CNN)

CNN is a deep learning algorithm specifically designed for image processing tasks. It automatically extracts important features such as edges, shapes, and textures from images using convolution layers. CNN eliminates the need for manual feature extraction and is highly effective in medical image analysis. In this project, CNN can be used to improve fracture detection accuracy by learning complex patterns in X-ray images. However, it requires more computational resources and training time.

4.1.3 BACKPROPAGATION NEURAL NETWORK (BPNN)

In this project, BPNN is used for classification tasks where it learns relationships between input features and output classes. It is suitable for nonlinear data and can model complex patterns. However, it requires careful tuning of parameters such as learning rate and number of hidden layers, and the training process can be time-consuming.

.4.1.4 SYSTEM MODULES

The system is divided into the following modules:

- Dataset Upload Module
- Preprocessing Module
- Feature Extraction Module
- Train-Test Split Module
- Model Training Module
- Prediction Module

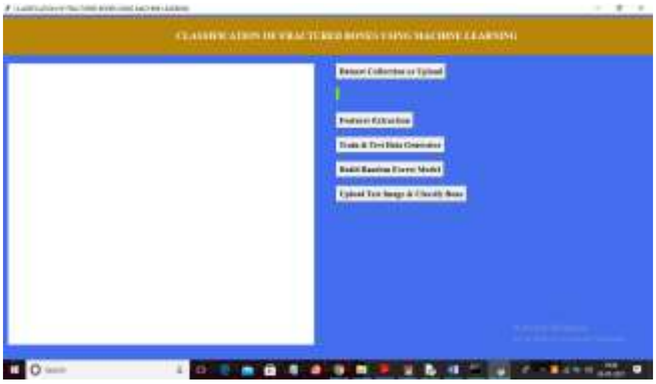
4.1.5 DECISION TREE

Decision Tree is a supervised machine learning algorithm used for classification tasks that works by splitting the dataset into smaller subsets based on feature values, forming a tree-like structure of decisions. Each node represents a condition, and each branch represents the outcome, leading to a final class label at the leaf node. In this project, the Decision Tree algorithm can be used to classify bone types from X-ray images using extracted pixel features. It is simple to understand, easy to implement, and provides clear decision-making steps. However, it may suffer from overfitting when used alone, which can reduce accuracy on new data, but it is useful for understanding the classification process and comparing with other models.

V. EXPERIMENTAL RESULTS AND DISCUSSION

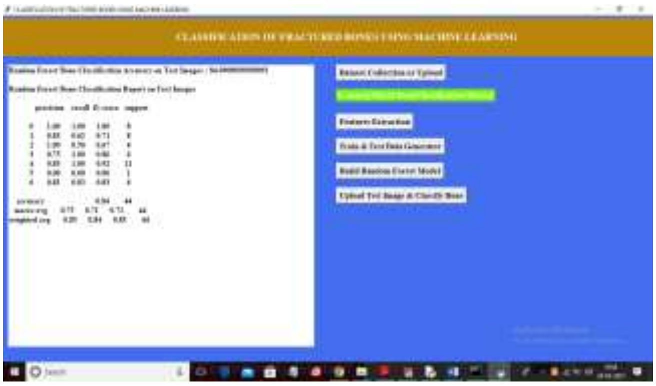
The system was tested using the MURA dataset with an 80:20 train-test split.
The Random Forest model achieved an accuracy of approximately 84%, showing reliable performance.
Evaluation metrics like precision, recall, and F1-score confirm effective classification.
The system successfully classifies bone types and displays results through a user-friendly interface.
Overall, the system is efficient, accurate, and can be improved further for complex cases.

System Interface – Home Page:



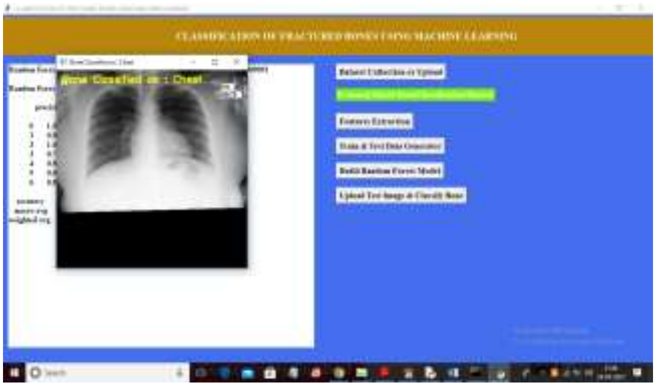
GUI Showing Successful Dataset Upload in Bone Fracture Classification System

Fig. 1.Accuracy Page.



GUI Displaying Random Forest Model Accuracy and Classification Report

Fig. 2. Final Output Page



Result of Bone Classification Using Random Forest Model

VI. CONCLUSION

In conclusion, the project successfully develops an efficient machine learning–based system for the classification of bone types using X-ray images. By utilizing image preprocessing, feature extraction, and the Random Forest algorithm, the system achieves reliable and accurate classification results. The implementation of an automated approach reduces manual effort, minimizes human error, and improves diagnostic speed. The system also provides a user-friendly interface for easy operation and real-time prediction. Overall, the proposed system demonstrates strong performance and has the potential to support healthcare professionals in accurate and timely diagnosis, with scope for further improvement using advanced techniques and larger datasets..

VII. FUTURE SCOPE

The proposed system can be further enhanced in several ways to improve its performance and real-world applicability. Advanced deep learning techniques such as Convolutional Neural Networks (CNN) and transfer learning can be implemented to achieve higher accuracy in fracture detection. The dataset can be expanded to include more diverse and complex bone fracture cases, which will improve the model's generalization ability. Real-time integration with hospital systems and radiology tools can make the system more practical for clinical use. Additionally, deploying the system as a web or mobile application can increase accessibility for healthcare professionals. Further improvements can include better visualization of fracture regions and explainable AI techniques to assist doctors in decision-making. Overall, these enhancements will make the system more robust, scalable, and suitable for real-world medical applications.

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