FRACTURE DETECTION USING MACHINE LEARNING

TEAM MEMBERS:

NANDEESH H U– 234161018

MANIKANTHA DANDI – 234161017

BHUSHAN PATIL – 234161015

PUSHPENDER KUMAR- 234161020

AMAN KUMAR - 234161001

GUIDED BY:

Dr. DEBANGA RAJ NEOG

PROBLEM STATEMENT

BACKGROUND

Traditional X-ray imaging, while fundamental in diagnosing skeletal injuries, often falls short due to inherent limitations in image clarity and detail. This lack of precision can lead to misinterpretations and overlooked bone fractures, posing significant risks to patient care. Additionally, real-world medical imaging is frequently marred by noise and inconsistencies, which compound the challenges faced by medical professionals. These issues not only hinder diagnostic accuracy but also escalate healthcare costs due to misdiagnoses and the need for repeated imaging.

CHALLENGES

1. **Blurry Vision in Conventional X-rays:** Traditional X-ray methods do not provide the necessary detail for accurate bone fracture diagnosis, leading to potential misinterpretations and missed diagnoses.
2. **Noisy Data in Medical Imaging:** X-ray images often contain imperfections such as noise and inconsistencies, further complicating the diagnostic process and affecting decision-making by healthcare professionals.
3. **Decision Dilemma:** The combination of unclear visuals and uncertain data leaves medical professionals grappling with difficult diagnostic decisions, impacting patient outcomes.
4. **Need for Enhanced Image Quality:** There is a critical need for robust preprocessing techniques that can cleanse and improve the quality of X-ray images, enabling better analysis and clearer diagnostics.

PROPOSED SOLUTIONS

The project proposes the development of an advanced, machine learning-based system for the automated detection of bone fractures. This system aims to:

- **Improve Diagnostic Accuracy:** By leveraging sophisticated machine learning algorithms and enhanced image preprocessing methods, the system will address the limitations of traditional X-ray imaging.
- **Enhance Decision-Making:** The system will provide clearer, more consistent diagnostic results, reducing uncertainty and aiding medical professionals in making informed decisions.
- **Reduce Healthcare Costs:** By improving the accuracy of initial diagnoses, the system will decrease the need for repeat scans and follow-up procedures, thereby reducing overall healthcare expenditures.
- **Improve Patient Understanding and Care:** The system will present diagnostic results in a visually understandable format, making it easier for patients and clinicians to discuss treatment options and outcomes.

IMPACT

Enhancing the accuracy and efficiency of bone fracture diagnosis through innovative machine learning techniques is crucial not only for improving patient care but also for advancing the capabilities of diagnostic technology within the healthcare industry. By integrating advanced algorithms and computational methods into the diagnostic process, this initiative addresses critical challenges that currently limit the effectiveness of traditional imaging methods. Accurate diagnoses ensure that patients receive appropriate and timely treatments, significantly reducing the risk of complications associated with undetected or misdiagnosed fractures. This precision also minimizes unnecessary treatments, which can often be invasive and costly, thus protecting patients from potential side effects and further health complications. Furthermore, by setting a precedent for the adoption of artificial intelligence in medical imaging, this project enhances the overall capabilities of diagnostic tools, making them more sensitive to subtle indications of issues that may be overlooked by the human eye.

The application of sophisticated machine learning models like Random Forest in the diagnosis of bone fractures contributes directly to more reliable diagnostics and better patient outcomes. Reliable diagnostics are especially critical in emergency settings where swift and accurate decisions can significantly impact patient recovery trajectories. With faster and more accurate diagnosis, the likelihood of long-term impairments due to delayed treatment is significantly reduced. Moreover, improving diagnostic efficiency can substantially lower healthcare costs by reducing the number of unnecessary procedures and follow-up appointments caused by initial diagnostic errors. As healthcare systems worldwide strive to optimize efficiency and reduce expenses, the successful implementation of this project not only demonstrates the potential savings from advanced diagnostic tools but also suggests broader applications for machine learning in enhancing healthcare delivery on a global scale.

RELATED WORK

In a notable study by Vishnu et al. (2017), a method for classifying long bone fractures was developed using the Bag of Words (BoW) model for initial feature extraction, followed by the application of a Support Vector Machine (SVM) for model training. This technique focused on distinguishing between transverse and oblique fractures, achieving a detection rate of 78% for both types. The study demonstrated the potential of combining traditional text analysis techniques with machine learning to enhance fracture detection in medical imaging.

Myint et al. (2018) explored various image processing techniques to identify and classify fractures in the tibia, the lower leg bone. Their system employed a three-stage process involving preprocessing, feature extraction, and classification. In the preprocessing phase, techniques like Unsharp Masking and the Harris algorithm were used for image sharpening and corner detection, respectively. For classification, a Simple Decision Tree was used to detect the presence of fractures, and a K-Nearest Neighbor algorithm was employed to categorize the fractures into Normal, Transverse, Oblique, and Comminuted, achieving an overall accuracy of 82%.

The 2019 study by Hržic et al. introduced a hybrid approach for identifying fractures in pediatric ulna and radius bones, demonstrating a high level of accuracy. The method involved comparing the extracted contour of the bone with an estimated contour of a healthy bone for fracture identification. This approach utilized local entropy for both de-noising the images and removing irrelevant tissue, followed by refined segmentation to pinpoint areas of interest. A local Shannon entropy calculation was then applied to each pixel within the image using a 2D sliding window, achieving an impressive 91% accuracy rate.

Yang & Cheng (2019) presented two innovative line-based fracture detection methods using artificial neural networks, which were specifically tailored to reduce the training data requirements. Their techniques involved extracting features based on recognized line patterns within X-ray images. The ADPO scheme, which outperformed the Standard scheme, optimized parameters of the Probabilistic Hough Transform to better detect granule lines in fractured regions. Each line detected contributed 13 distinct features to the classification process, with the ADPO scheme reaching an average accuracy of 72.89%. This study highlighted the efficiency of using neural networks for feature recognition and fracture detection.

DATASET

SOURCE AND COMPOSITION

The dataset for this project was sourced from Kaggle, featuring a collection of X-ray images specifically focused on the arms and legs. It comprises a total of 9,463 samples, which are categorized into two main groups: 4,840 images with fractures and 4,623 images without fractures. This diverse dataset provides a robust foundation for training and testing the machine learning models developed in this study.

DATA SPLIT

The dataset has been split into training and testing sets to facilitate the development and evaluation of the predictive models. Specifically, 80% of the data, equivalent to approximately 7,570 images, has been designated as the training set. This large training set is crucial for effectively training the machine learning algorithms by allowing them to learn from a wide range of examples, including both fractured and non-fractured X-rays. The remaining 20% of the data, about 1,893 images, constitutes the test set. This separation ensures that the model's performance is evaluated on new, unseen images, providing an unbiased assessment of its diagnostic accuracy.

This dataset not only supports the model training phase but also ensures that the evaluation phase is rigorous and reflective of real-world scenarios. The balanced nature of the dataset, with nearly equal numbers of fractured and non-fractured images, is particularly beneficial for reducing model bias towards any one class.

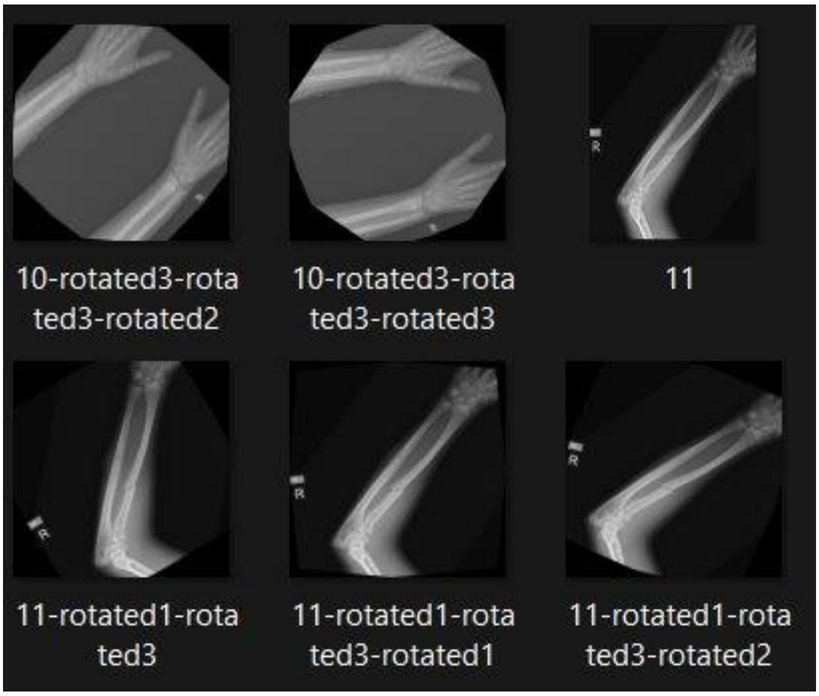

Figure 1: Datasets

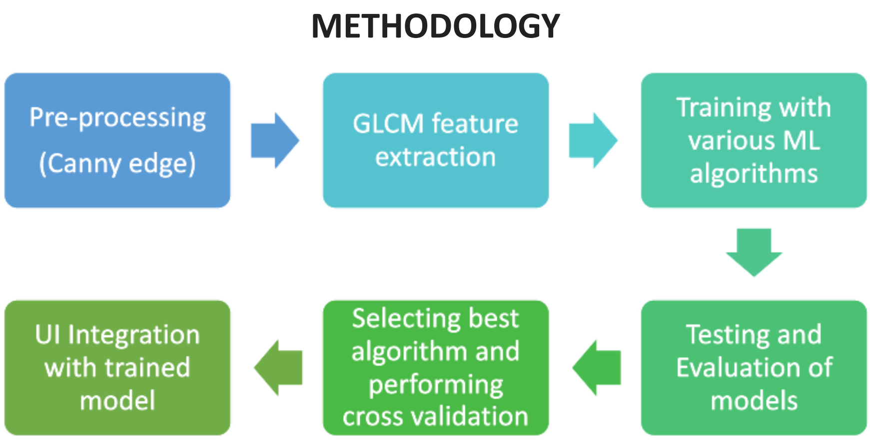

Figure 2: Methodology

1. PREPROCESSING WITH CANNY EDGE DETECTION

The first step in our methodology involves pre-processing the X-ray images to enhance the clarity and definition of fractures. We employ the Canny edge detection algorithm, renowned for its efficacy in highlighting sharp discontinuities in images while reducing noise. This algorithm works by identifying the intensity gradients in the images, which effectively delineate the edges of bones and potential fractures. By setting thresholds for the gradients, the algorithm isolates these edges from the rest of the image, which is crucial for accurately locating and assessing fractures.

2. GLCM FEATURE EXTRACTION

After edge enhancement, feature extraction is conducted using the Gray Level Co-occurrence Matrix (GLCM). GLCM analyzes the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, thereby providing a statistical view of texture. The features extracted from GLCM include:

- **Contrast:** Measures the local variations in the gray-level co-occurrence matrix.
- **Correlation:** Evaluates how correlated a pixel is to its neighbors over the whole image.
- **Energy:** Sum of squared elements in the GLCM.
- **Homogeneity:** Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

These features are critical as they help in distinguishing between normal and abnormal patterns in the bone structure, which is a key factor in identifying fractures.

3. TRAINING WITH VARIOUS ML ALGORITHM

Utilizing the features extracted, we proceed to train various machine learning algorithms. The choice of multiple algorithms is intentional to determine which model best handles the complexity and variability of the data. Among the algorithms tested are Support Vector Machines (SVM), which are effective in high-dimensional spaces, and Random Forests, known for their high accuracy and robustness to overfitting. Each model is trained using a subset of our data, allowing it to learn from both positive cases (fractures) and negative cases (no fracture).

4. TESTING AND EVALUATION OF MODEL

Post-training, each model is subjected to a rigorous testing phase using unseen data. This step is vital to ascertain the generalizability of the models beyond the training data. We employ several metrics to evaluate the performance of each model:

- **Accuracy:** The proportion of true results among the total number of cases examined.
- **Precision and Recall:** Precision measures the accuracy of positive predictions, and recall measures the ability of the model to find all the relevant cases (all fractures).
- **F1 Score:** The harmonic mean of precision and recall, providing a balance between the two in cases of uneven class distribution.

5. SELECTING BEST ALGORITHM AND PERFORMING CROSS VALIDATION

Following the evaluation, the algorithm that exhibits the highest performance across our metrics is selected. To validate this choice and ensure the model's reliability, we conduct k-fold cross-validation. This method involves dividing the data into 'k' number of subsets and repeatedly training the model 'k' times, each time with a different subset held as the test set and the remaining as the training set. This process helps mitigate any potential overfitting and confirms the model's stability across different subsets of data.

6. UI INTERGRATION WITH TRAINED MODEL

The final step in our methodology is the integration of the selected, validated model into a user interface (UI) designed for clinical use. The UI allows medical professionals to easily upload new X-ray images and receive immediate, automated diagnostics. It displays the results in a visually accessible format, highlighting detected fractures and providing an assessment of the fracture type. This interface is designed to support fast, efficient decision-making in clinical settings, enhancing both the speed and accuracy of diagnostics.

EXPERIMENTS AND RESULTS

EXPERIMENTS SETUP

The experiments conducted in this project were meticulously designed to evaluate and compare the efficacy of various machine learning algorithms in the task of identifying bone fractures from X-ray images. The primary focus was to utilize a comprehensive set of features derived from the Gray Level Co-occurrence Matrix (GLCM), a statistical method of examining texture that considers the spatial relationship of pixels. This approach was chosen because of its ability to capture and quantify texture variations in the images, which are crucial for distinguishing between fractured and non-fractured bones.

Before feature extraction, each image underwent pre-processing using the Canny edge detection algorithm. This method is particularly noted for its effectiveness in reducing noise and emphasizing the structure of the object within the image by highlighting its edges. By isolating these edges, the algorithm prepares the image for a more detailed analysis, improving the subsequent feature extraction process with GLCM. The enhanced contrast and focus on boundaries make it easier for the subsequent algorithms to analyze the textural and structural differences indicative of fractures.

The machine learning algorithms selected for testing were chosen for their diverse strengths and applicability to the problem at hand:

- **Support Vector Machine (SVM):** This algorithm is renowned for its proficiency in handling high-dimensional spaces, which is typical of image-based feature sets. SVM works by finding the hyperplane that best separates the classes of data points, making it particularly suited for complex classification tasks where the distinction between classes is not immediately apparent.
- **Decision Tree:** Known for its straightforward interpretability, the Decision Tree algorithm offers clear decision rules that are easy to understand and implement. This method breaks down a

dataset into smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes, which make it highly effective for rule-based decision-making.

- **Naïve Bayes:** This probabilistic classifier assumes independence between predictors and applies Bayes' Theorem to predict the category of a given sample. It is known for its simplicity and effectiveness, especially in large datasets where the underlying conditional probabilities can be reliably estimated.
- **Random Forest:** As an ensemble method, Random Forest improves classification accuracy by building multiple decision trees and merging them together to obtain a more stable and accurate prediction. Random Forests correct for decision trees' habit of overfitting to their training set, providing a more generalized solution.
- **K-Nearest Neighbors (KNN):** KNN is a non-parametric method used for classification and regression. For classification, the output is a class membership determined by a majority vote of the nearest neighbors; each object is assigned to the class most common among its k nearest neighbors.
- **Logistic Regression:** Often used for binary classification problems, Logistic Regression measures the relationship between the categorical dependent variable and one or more independent variables by estimating probabilities using a logistic function, which is an essential characteristic of binary outcomes.
- **K-means Clustering:** Utilized in this context as an unsupervised method, K-means aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean. This method was explored to potentially identify distinct clusters that could represent fracture versus non-fracture patterns based on unsupervised classification of features.

Each of these algorithms was selected not only for its unique strengths but also for the potential to complement the others in achieving the most accurate results in fracture identification, addressing the project’s primary goal to enhance diagnostic capabilities in medical imaging.

TESTING AND MODEL EVALUATION

In this project, the robustness and efficacy of different machine learning algorithms were evaluated through a comprehensive testing and evaluation phase. To conduct this evaluation, the dataset was divided into two distinct sets: 80% was used for training the models, allowing them to learn and adapt to the nuances of the X-ray images depicting bone fractures, and the remaining 20% was reserved for testing. This division ensured that the evaluation was performed on unseen data, providing a realistic measure of how each algorithm would perform in real-world diagnostic scenarios.

KEY PERFORMANCE METRICS

The performance of each machine learning model was assessed using a variety of statistical metrics, each chosen for its relevance to the medical diagnostic context, where accuracy, reliability, and the minimization of errors are paramount:

- **Precision:** This metric is particularly crucial in medical diagnostics, where the cost of false positives can be high—not only in terms of economic impact but also in terms of patient stress and the potential for unnecessary treatments. Precision measures the accuracy of positive predictions, that is, the proportion of positive identifications that were actually correct. A high precision rate indicates that an algorithm is effective at reducing false positives, thus ensuring that patients are only subjected to further procedures when necessary.

- **Recall:** Also known as sensitivity, recall is essential for medical applications because it measures the ability of the model to detect all actual positives correctly. In the context of fracture detection, a high recall rate means that the system is capable of identifying most of the fractures present in the X-ray images, thus minimizing the risk of missing a diagnosis that could lead to improper or delayed treatment.
- **Accuracy:** This metric provides an overall indication of the model's effectiveness across all classifications. It represents the ratio of true results (both true positives and true negatives) in the dataset, offering a straightforward measure of performance. In medical imaging, high accuracy ensures that the model performs well in identifying both fractures and non-fractures accurately.
- **F1 Score:** Because medical datasets can often be imbalanced, with non-fracture cases perhaps outnumbering actual fractures, the F1 Score becomes particularly useful. It is the harmonic mean of precision and recall, providing a single metric that balances both. The F1 Score is especially important in scenarios where both false positives and false negatives carry significant consequences, as it ensures that a model does not overly favor one class over another.
- **AUC Score:** The Area Under the Curve (AUC) Score is derived from the receiver operating characteristic (ROC) curve and provides a comprehensive measure of a model's ability to discriminate between the classes at various threshold levels. A high AUC Score indicates that the model can effectively distinguish between the fractured and non-fractured classes across a range of decision thresholds, which is crucial for tuning the model according to different clinical sensitivities and specificities.

IMPORTANCE OF COMPREHENSIVE METRICS

By employing these diverse metrics, the project ensures a holistic evaluation of each model's capabilities, allowing for refined judgments on their suitability for deployment in clinical settings. This multi-metric approach not only highlights the strengths and weaknesses of each algorithm but also aligns the evaluation process closely with the practical needs and realities of medical diagnostics, where the consequences of errors can be significant. Each metric provides a different perspective on the model's performance, ensuring that the chosen algorithm not only performs well statistically but also meets the high standards required for medical applications.

DETAILED RESULTS

The detailed results from the testing and evaluation phase of the project clearly highlighted the distinct performance characteristics of the machine learning models applied, with Random Forest emerging as the most balanced and effective model for the task of bone fracture detection in X-ray images.

- **Random Forest Model:** Random Forest demonstrated superior performance metrics across the board but particularly excelled in balancing precision and recall, achieving high scores in both. This balance is critical in medical diagnostics, where the ability to differentiate between positive (fractured) and negative (non-fractured) cases accurately is as important as detecting as many true positive cases as possible without increasing false positives. The high precision indicates that when the Random Forest model predicts a fracture, it is highly likely to be correct, thus minimizing unnecessary medical interventions that could follow a false positive diagnosis. Similarly, its high recall rate ensures that the model misses very few actual fractures, crucial for patient care where every missed fracture could mean a delay in treatment with potentially serious implications for the patient.

- **Logistic Regression Model:** Logistic Regression, while showing exceptional recall, did so at the expense of precision. This model was highly effective at identifying most of the actual fracture cases, as evidenced by its recall rate, making it potentially useful in preliminary screening settings where missing a fracture would be unacceptable. However, the lower precision suggests that it also incorrectly labeled many non-fracture cases as fractures. In clinical practice, this tendency could lead to over-testing and unnecessary treatments, increasing healthcare costs and potentially exposing patients to unwanted procedures.
- **K-Means Clustering:** K-means Clustering showed interesting results with high recall but only moderate precision. This model's high recall indicates its effectiveness in identifying fractures, yet the moderate precision suggests a propensity to over-classify images as having fractures. This characteristic might make K-means suitable for initial screening phases in a diagnostic pipeline where the goal is to catch as many potential fractures as possible, understanding that a subsequent, more precise test will be used to confirm these findings. However, like with Logistic Regression, the risk of false positives cannot be overlooked, as it could lead to similar clinical and operational inefficiencies.

IMPLICATIONS OF RESULTS

The outcomes of these tests underscore the importance of selecting the right model based on the specific requirements and constraints of the application environment. For environments where the cost of a false positive is high, Random Forest offers the best trade-off between identifying fractures accurately and avoiding false alarms. Conversely, in settings where missing a fracture is more critical, models with higher recall like Logistic Regression and K-means might be considered as part of a multi-tiered diagnostic approach, where they serve as preliminary screening tools rather than definitive diagnostic solutions.

The detailed results from this study provide valuable insights into how different machine learning models handle the complexities of fracture detection in X-ray imaging, guiding future applications and development in medical diagnostic technology.

- **Random Forest** proved superior, with precision, recall, and accuracy significantly higher than other models, suggesting it was best at managing the trade-off between sensitivity and specificity.
- **Logistic Regression** showed exceptional recall but at the cost of lower precision, which may be problematic in a clinical setting where false positives can lead to unnecessary treatments.
- **K-means** demonstrated high recall but moderate precision, indicating a tendency to over-classify images as fractures.

ML Algorithm	Precision	Recall	Accuracy	F1 Score	AUC Score
SVM	55.41%	89.58	67%	68.46%	70.76%
Decision Tree	53.6%	67.5%	63.66%	59.75%	64.3%
Naïve Bayes	60.7%	89.58%	72.66%	72.36%	75.48%
Random Forest	73.26%	83.33%	81.16%	77.97%	81.52%
K-Nearest Neighbors	65.97%	80%	59%	72.31%	62.5%
Logistic Regression	49.57%	96.25%	59.33%	65.43%	65.48%
K-means	58.64%	97.5%	71.5%	73.23%	75.83%

Table 1: Model Evaluation

CROSS VALIDATION AND FINAL MODEL SELECTION

Following initial testing, the Random Forest model was subjected to k-fold cross-validation to verify its consistency across multiple subsets of data. This process confirmed the model's robustness and reliability, with consistently high scores across all metrics, including a standout AUC score of 95.55%, indicating excellent model discrimination capabilities.

Parameter	Result
No of estimators	84
Precision	88.91%
Recall	85.97%
Accuracy	88.90%
F1 Score	87.41%
AUC Score	95.55%

Table 2: Cross Validation Results

USER INTERFACE INTEGRATION AND REAL WORLD APPLICATION

The validated Random Forest model was then integrated into a user-friendly graphical interface designed for clinical use. This interface supports rapid diagnostics by allowing medical professionals to upload X-ray images and receive immediate, clear, and reliable feedback on potential fractures.

- **UI Design:** Features a simple layout with functional elements that allow users to easily upload images and view results.
- **Functionality Testing:** The interface was tested with a variety of X-ray images to ensure accurate and consistent performance. Test images included both clear fractures and borderline cases to assess the model's diagnostic precision.
- **Feedback Mechanism:** The interface includes options for users to provide feedback on the accuracy of the diagnosis, which can be used to further train and refine the model.

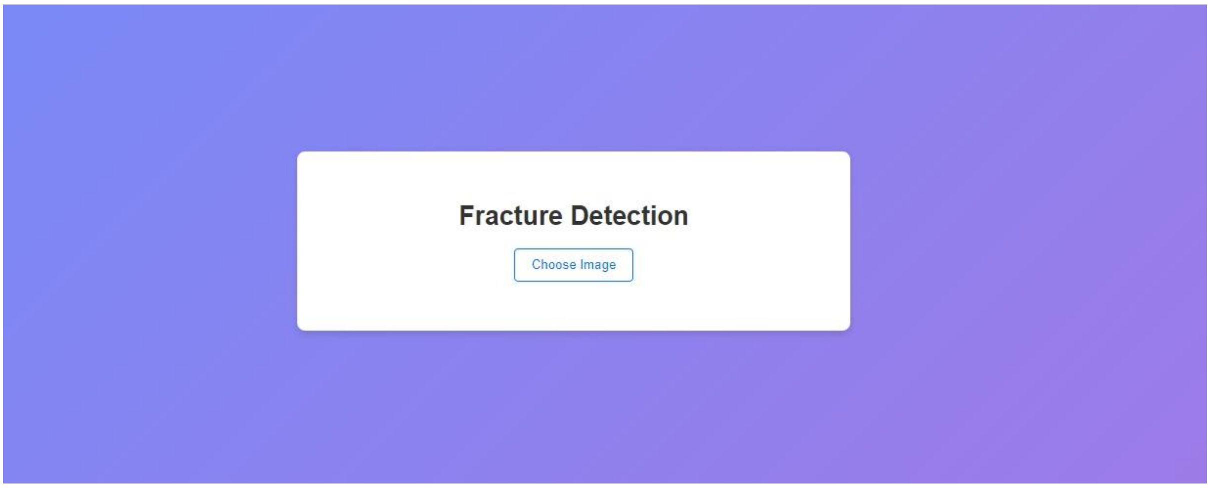

Figure 3: UI Interface 1

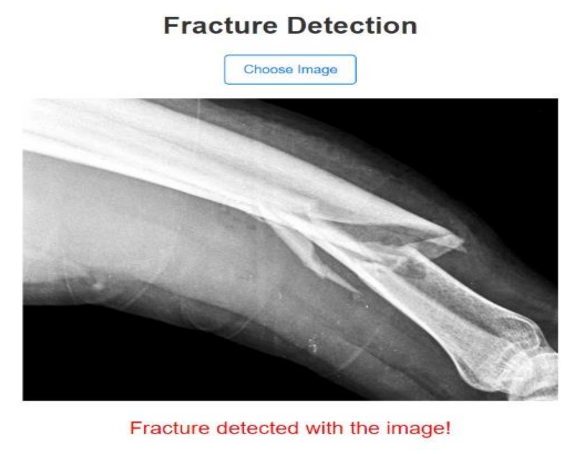

Figure 4: UI Interface 2

Figure 5: UI Interface 3

CONCLUSION

This project set out to address critical issues in the accuracy and efficiency of bone fracture detection from X-ray images, a fundamental challenge in the medical field. By leveraging advanced machine learning techniques and robust feature extraction methods, we sought to develop a system that not only improves diagnostic accuracy but also reduces the risk of missed fractures, thereby enhancing patient care and reducing potential complications from undiagnosed conditions.

MODEL PERFORMANCE AND EVALUATION

Throughout our experiments, the focus was on comprehensively evaluating each model's ability to correctly classify bone fractures. Emphasis was placed on Accuracy and Recall metrics to ensure that the models not only identify the presence of fractures accurately but also minimize the number of fractures that go undetected. Random Forest emerged as the most effective model, demonstrating consistently high performance across all key metrics. It achieved an accuracy of 81.16% and a recall of 83.33% during initial testing, with further validation through cross-validation enhancing these scores to 88.90% and 85.97%, respectively.

ADVANTAGES OF RANDOM FOREST

The superiority of the Random Forest model in our tests can be attributed to its ensemble approach, which combines multiple decision trees to reduce overfitting and increase the model's generalizability. This was particularly evident in its high F1 Score and AUC Score, which were 87.41% and 95.55% respectively, indicating an excellent balance between precision and recall — crucial for medical diagnostic tools where both identifying positives and minimizing false negatives are important.

IMPACT ON MEDICAL DIAGNOSTICS

Integrating this model into a user-friendly interface has allowed us to create a tool that is not only technologically advanced but also practical and accessible for medical professionals. The interface simplifies the process of diagnosing fractures, making it faster and more reliable. This reduces the workload on radiologists and potentially speeds up the treatment process for patients, contributing to better healthcare outcomes. Furthermore, the reduction in missed fractures can significantly decrease the risk of complications arising from untreated injuries, underlining the importance of accurate diagnostic systems in medical practice.

FUTURE DIRECTION

While the current system represents a significant advancement, future work can expand its capabilities and applications. Potential improvements include the incorporation of more diverse datasets encompassing a wider variety of fracture types and more complex cases. Additionally, employing deep learning algorithms could offer improvements in feature detection and classification accuracy. Further research into user interface enhancements would also be beneficial, focusing on increasing interactivity and providing more detailed feedback to users.

In conclusion, the successful development and implementation of this bone fracture detection system mark a significant step forward in the use of machine learning in medical imaging. By addressing key challenges with innovative solutions, this project not only enhances diagnostic accuracy but also supports the broader goals of improving patient care and operational efficiency in healthcare settings.

GITHUB LINK: https://github.com/manikantha-dandi/IPML-Project

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