Chest X-Ray Disease Classification

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***Abstract*— This research presents an automated, hybrid machine learning and deep learning system for chest X-ray disease classification, aiming to improve diagnostic accuracy and streamline clinical workflows. The system addresses fracture detection, pneumonia prediction, and multi-disease classification using a combination of traditional machine learning and deep learning techniques.**

For fracture detection, Histogram of Oriented Gradients (HOG) features are used with an SVM classifier. Pneumonia prediction employs a Convolutional Neural Network (CNN), while multi-disease classification combines SVM, Random Forest (RF), and an ensemble model to classify conditions like pneumonia, fibrosis, and cardiomegaly. Data preprocessing techniques, such as image normalization and augmentation, enhance model performance.

The system is integrated into a Flask-based web application, allowing healthcare professionals to upload chest X-rays and receive real-time predictions. This hybrid model, combining the strengths of HOG+SVM and CNN, balances accuracy and computational efficiency, reducing radiologists' workload, improving diagnostic accuracy, and enabling early detection of critical conditions. The research suggests future potential in expanding to other medical imaging domains and integrating with healthcare infrastructure.

Keywords— Machine learning, deep learning, chest X-ray, disease classification, fracture detection, pneumonia prediction, multi-disease classification, Support Vector Machine (SVM), Convolutional Neural Network (CNN), Random Forest (RF), Flask, medical image processing, disease detection, automated diagnostics.

I. INTRODUCTION

Chest X-rays are one of the most widely used diagnostic tools in medical imaging, providing valuable insights into various pulmonary diseases, bone fractures, and other health conditions. Manual analysis of chest X-ray images is a time-consuming task for radiologists, requiring high levels of expertise. However, the subjective nature of human interpretation can lead to errors or delayed diagnoses. To address these challenges, the application of machine learning (ML) and deep learning (DL) models in medical imaging has gained significant attention. These models can automate the process of disease classification, providing rapid and accurate results that assist healthcare professionals in making timely decisions. This research aims to develop an automated system for classifying diseases from chest X-ray images using various machine learning techniques. The system comprises three sub-projects: fracture detection, pneumonia prediction, and multi-disease classification, each focusing on a specific disease category. The fracture detection model uses traditional machine learning techniques like Support Vector Machine (SVM) and Histogram of Oriented Gradients (HOG) for feature extraction. For pneumonia prediction, a Convolutional Neural Network (CNN) is implemented to classify chest X-rays into normal or pneumonia-infected categories. The multi-disease classification model combines machine learning methods, such as SVM and Random Forest (RF), in an ensemble approach to classify multiple diseases, including pneumonia, fibrosis, and cardiomegaly. Additionally, the models are integrated into a user-friendly web application built with Flask. The application enables healthcare providers to upload chest X-ray images and receive disease predictions in real-time, facilitating rapid decision-making in clinical settings. The combination of machine learning, deep learning, and web-based deployment aims to create a powerful tool that improves diagnostic accuracy and workflow efficiency in healthcare environments.

This paper discusses the methodology, results, and performance of the developed models, highlighting the potential of machine learning and deep learning in revolutionizing medical diagnostics.

II. LITERATURE REVIEW

The paper [1] discusses an innovative diagnostic technique that leverages advanced artificial intelligence to differentiate between COVID-19 and viral pneumonia using chest X-ray images. The authors, A. Al-Ghraibah et al., employed feature extraction methods such as Wavelet analysis, Scale Invariant Feature Transformation (SIFT), and Mel Frequency Cepstral Coefficient (MFCC). They utilized support vector machines (SVM) and artificial neural networks (ANN) for classification, achieving accuracy rates of up to 99%. This approach offers a rapid and precise alternative to traditional diagnostic methods, which can be time-consuming and complex.

The author of paper [2], M. Salehi et al., explores the use of deep transfer learning for the automated detection of pneumonia in pediatric chest X-rays. The study fine-tuned pre-trained convolutional neural networks to adapt to the pediatric dataset, aiming to enhance diagnostic accuracy and reduce reliance on manual interpretation. This method addresses the challenges of limited labeled pediatric data by leveraging knowledge from existing models trained on large datasets. The results indicate a promising approach to improving early diagnosis and treatment planning for pediatric pneumonia.

In paper [3], K. A. Phung and colleagues introduce a doctor consultation-inspired model designed to enhance disease recognition in X-ray images. This approach aims to replicate the diagnostic reasoning of medical professionals by integrating machine learning techniques that mimic expert consultations. The model focuses on improving the interpretability and accuracy of automated diagnostics, potentially serving as a supportive tool for clinicians in identifying various conditions from radiographic images.

The authors of paper [4], S. Deshmukh and P. Bhalchandra, present a deep learning-based system for pneumonia detection, seamlessly integrated with the Flask web framework. This integration facilitates the development of a user-friendly web application capable of real-time diagnostic processing. By deploying convolutional neural networks trained on chest X-ray datasets, the system aims to provide accessible and efficient diagnostic support, particularly in resource-limited settings where rapid decision-making is crucial.

Paper [5] by W. Liawrungrueang et al. delves into the application of convolutional neural networks (CNNs) for detecting cervical spine fractures from medical imaging. The study focuses on developing a model that can accurately identify fractures, thereby assisting in trauma diagnosis. By training the CNN on a dataset of cervical spine images, the authors aim to enhance the speed and precision of fracture detection, which is critical in emergency medical scenarios.

In paper [6], M. A. Hasnain and co-authors conduct a systematic comparison of various deep learning architectures applied to dental diagnostics. The research evaluates multiple models to determine their effectiveness in predicting dental diseases through X-ray imaging. By analyzing performance metrics across different architectures, the study provides insights into the most suitable deep learning approaches for accurate and efficient dental disease diagnosis, potentially informing future developments in dental healthcare technology.

The author of paper [7], S. S. S. R. Depuru et al., apply support vector machine (SVM) techniques for data classification in the context of detecting electricity theft. The study showcases the versatility of SVM in analyzing consumption patterns to identify irregularities indicative of theft. By implementing this machine learning approach, utility companies can enhance their ability to detect and prevent unauthorized usage, thereby reducing losses and improving the efficiency of electricity distribution systems.

Paper [8] by A. S. M. Al Islam and colleagues introduce a convolutional neural network (CNN)-based method aimed at the automated detection of bone fractures from X-ray images. The study focuses on developing a model that can accurately identify fractures, assisting healthcare professionals in making rapid and precise diagnoses. By training the CNN on a diverse set of X-ray images, the approach seeks to improve diagnostic workflows and patient outcomes in orthopedic care.

In paper [9], R. Siddiqi and S. Javaid provide a

comprehensive survey of deep learning techniques utilized for pneumonia detection in chest X-ray images. The review examines various models and methodologies, highlighting recent advancements and ongoing challenges in the field. The authors discuss the potential of deep learning to enhance diagnostic accuracy and efficiency, as well as the need for large, annotated datasets and considerations regarding model interpretability in clinical settings.

The authors of paper [10], M. F. F. Mardianto et al., explore the combination of support vector machines (SVM) and convolutional neural networks (CNN) for the classification of pneumonia from chest X-ray images. The study aims to optimize feature extraction and improve detection accuracy by leveraging the strengths of both machine learning techniques. By integrating SVM and CNN, the proposed model seeks to enhance the reliability of pneumonia diagnosis, potentially aiding in more effective patient management and treatment strategies.

Paper [11] by H. K. Ahmad and co-authors present a systematic review focusing on the augmentation of chest X-ray interpretation through machine learning. The review examines various studies that integrate machine learning algorithms into radiological assessments, evaluating their potential to enhance diagnostic performance. The authors discuss the benefits of machine learning in improving accuracy and efficiency, as well as the challenges related to implementation, such as data quality, algorithm transparency, and integration into existing clinical workflows.

In paper [12], S. Park and colleagues concentrate on enhancing the classification of lung diseases from chest X-ray images using machine learning techniques. The study involves developing robust models capable of accurately distinguishing between different pulmonary conditions. By training these models on labeled datasets, the research aims to support healthcare professionals in making precise diagnoses, thereby improving patient care and facilitating timely interventions for various lung diseases.

CHALLENGES

In the realm of automated disease classification using chest X-ray images, several significant challenges have been identified across various studies. A primary concern is the limited availability of labeled medical imaging data, which is essential for training robust machine learning models. This scarcity often leads to models that are prone to overfitting and may not generalize well to unseen data. Additionally, the inherent variability in image quality, stemming from differences in imaging equipment and patient positioning, poses difficulties in achieving consistent and accurate feature extraction. Feature extraction itself is a critical challenge; traditional methods may fail to capture the complex patterns associated with various diseases, while deep learning approaches require substantial computational resources and large datasets to effectively learn these features. Moreover, ensuring the interpretability of model predictions remains a concern, as black-box models can hinder clinical acceptance and trust.

III. METHODOLOGY

This research aims to develop a machine learning-based system for classifying diseases from chest X-ray images. The system involves three sub-projects: fracture classification, pneumonia detection, and multiple disease classification. Each sub-project utilizes different machine learning and deep learning techniques for effective image analysis. The overall methodology consists of data collection, preprocessing, feature extraction, model development, evaluation, and web-based deployment. The following steps outline the methodology for each sub-project and their integration into a single web application.

Data Collection and Preprocessing:
Fracture Detection: The dataset is composed of X-ray images labeled as "fractured" or "non-fractured." Images are resized to a uniform size of 128x128 pixels for consistent input into the feature extraction pipeline. Histogram of Oriented Gradients (HOG) is used to extract image features that can effectively represent the structural patterns in the X-ray images.

Pneumonia Prediction: The dataset is derived from chest X-ray images labeled as either "Normal" or "Pneumonia." Image preprocessing involves resizing images to 256x256 pixels and rescaling pixel values to the range [0, 1] to ensure uniformity and improve model training. Data augmentation techniques such as random flips and rotations are applied to increase the dataset's diversity and improve generalization.

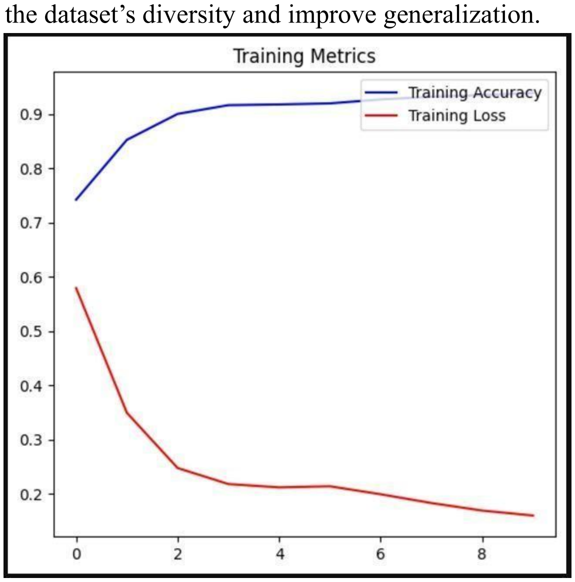

Fig. 1 Training Accuracy and Loss Graph

Multiple Disease Classification: The NIH Chest X-ray dataset is used, consisting of multi-labeled X-ray images with disease annotations such as pneumonia, nodule, infiltration, and others. Images are resized to 224x224 pixels and converted to a 3-channel format (RGB) for compatibility with the VGG16 model.
MultiLabelBinarizer is employed to handle the multi-label classification, converting categorical labels into a binary matrix format.

Proposed Contribution
For fracture detection, Histogram of Oriented Gradients (HOG) is utilized for feature extraction, enabling efficient structural pattern recognition. In pneumonia prediction, images are resized to 256x256 pixels, normalized to [0,1], and augmented with random flips and rotations to enhance generalization. For multiple disease classification, MultiLabelBinarizer is employed for multi-label handling, and grayscale images are converted to 3-channel RGB for VGG16 compatibility. This hybrid approach integrates HOG-based feature extraction, task-specific preprocessing, and multi-label classification, improving robustness and adaptability.

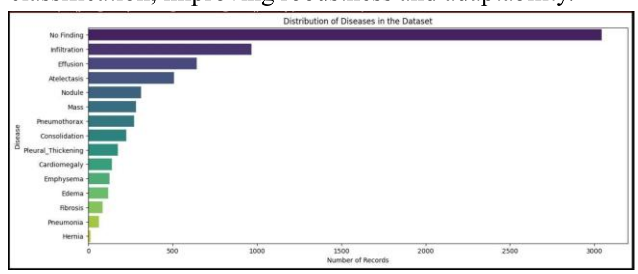

Fig. 2 Sample Frequencies for Each Class

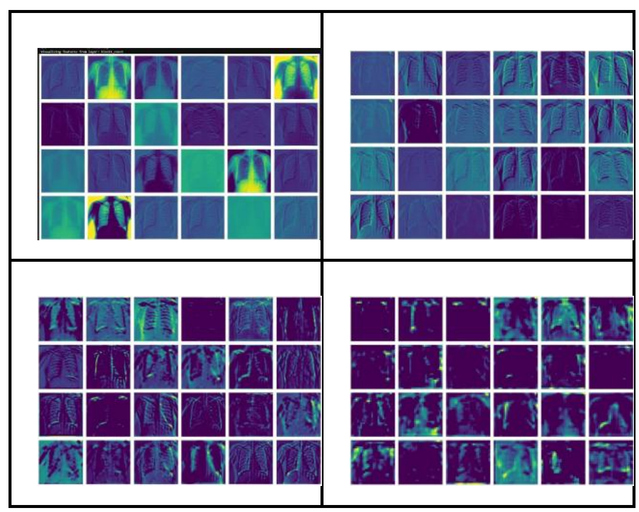

Fig. 3 Multi-Disease Classification Framework

Feature Extraction:
Fracture Detection: The HOG method is applied to extract features from the X-ray images. These features are then used for training a Support Vector Machine (SVM) classifier to predict whether a bone is fractured or not.

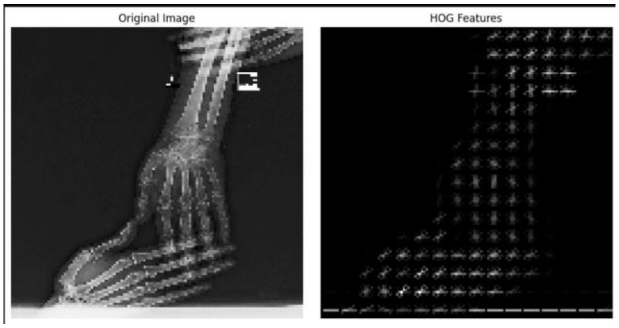

Fig. 4 Histogram of Oriented Gradients (HOG) Feature
Extraction for Fracture Detection

Pneumonia Prediction: A Convolutional Neural Network (CNN) model is utilized for feature extraction. Several convolutional layers are used to detect complex patterns and features in the images, followed by pooling layers to reduce dimensionality.

Multiple Disease Classification: The VGG16 pre-trained model is used as a feature extractor. The top layers of the model are removed, and the extracted features are used to train machine learning classifiers (SVM, Random Forest). The ensemble model combines the strengths of both classifiers to enhance performance.

Proposed Contribution

For fracture detection, HOG-based feature extraction is combined with an SVM classifier, offering a lightweight yet effective approach for structural analysis. In pneumonia prediction, a CNN-based feature extractor is employed, leveraging convolutional layers to detect intricate patterns in X-rays. For multiple disease classification, the VGG16 pre-trained model is repurposed by removing its top layers, extracting deep features that are then classified using an ensemble of SVM and Random Forest, enhancing robustness and performance. This integration of traditional ML (HOG+SVM) and deep learning (CNN, VGG16) optimizes accuracy while balancing computational efficiency.

Model Development:

Fracture Detection: An SVM classifier is trained using the extracted HOG features. The model is optimized using a linear kernel and the *probability=True* option to allow for probabilistic predictions.

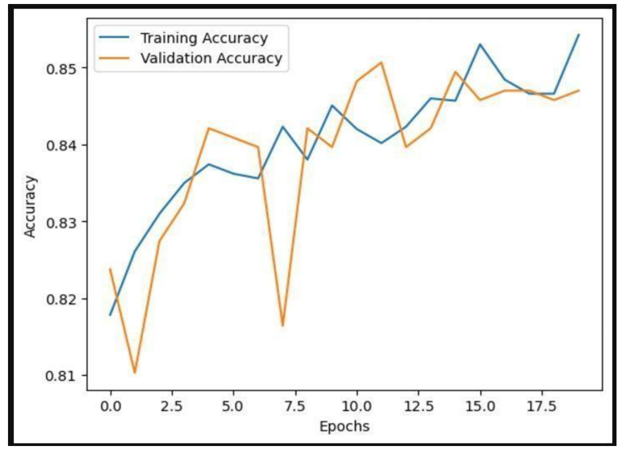

Fig. 5 Support Vector Machine (SVM) Model Architecture for Fracture Detection

Pneumonia Prediction: A CNN model is developed using Keras with multiple convolutional layers, pooling layers, and a fully connected output layer. The model is trained using the Adam optimizer and sparse categorical cross-entropy loss function.

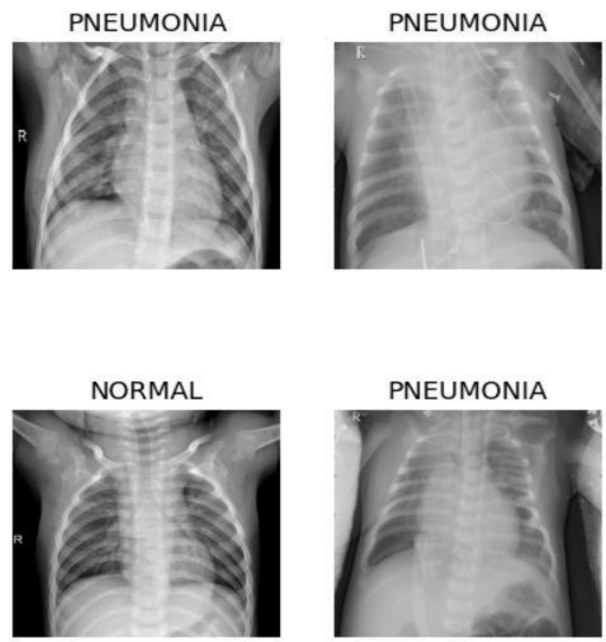

Fig. 6 Convolutional Neural Network (CNN) Model for
Pneumonia Prediction

Multiple Disease Classification: Three models are trained: SVM, Random Forest, and an ensemble model combining both. The ensemble model uses soft voting to combine predictions from both classifiers, improving overall accuracy and robustness.

Proposed Contribution

For fracture detection, an SVM classifier is trained on HOG features, optimized with a linear kernel and probabilistic outputs, enhancing interpretability. In pneumonia prediction, a CNN model is developed using Keras, incorporating multiple convolutional and pooling layers, trained with the Adam optimizer and sparse categorical cross-entropy, ensuring efficient learning. For multiple disease classification, an ensemble model integrates SVM and Random Forest with soft voting, leveraging both models' strengths to enhance accuracy and robustness. This combination of traditional ML and deep learning optimizes predictive performance across different classification tasks.

Model Evaluation:

Fracture Detection: The model is evaluated based on accuracy, precision, recall, and F1-score using a test dataset that was separated during preprocessing. An accuracy of 81% is achieved on the test set, demonstrating the model's ability to distinguish between fractured and non-fractured images.

Fig. 7 Fracture Detection Model Performance: Accuracy and Metrics

Fig. 8 Confusion Matrix for Fracture Detection Model Pneumonia Prediction: The model's performance is evaluated using accuracy as the primary metric. The model achieves a training accuracy of 85.40%, with a loss of 0.3657, indicating effective learning and model convergence.

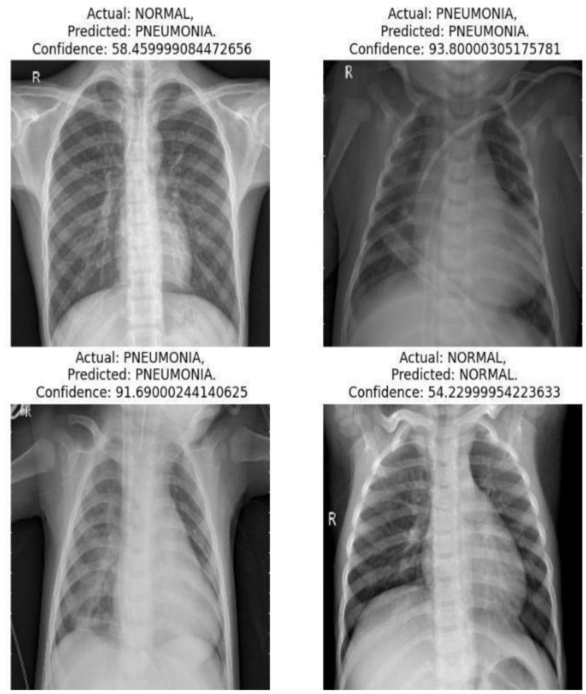

Fig. 9 Training Accuracy and Loss Curve for CNN Pneumonia Prediction Model

Multiple Disease Classification: The SVM, Random Forest, and ensemble models are evaluated based on accuracy, precision, recall, and F1-score. The ensemble model outperforms individual classifiers, making it the most effective model for handling multi-label classification tasks, especially with imbalanced data.

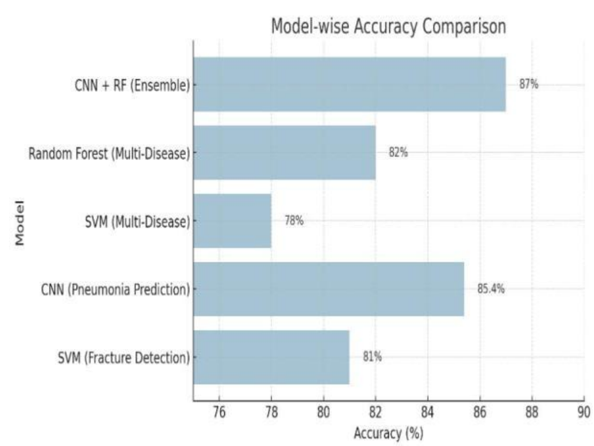

Fig. 10 Model-wise Accuracy Comparison

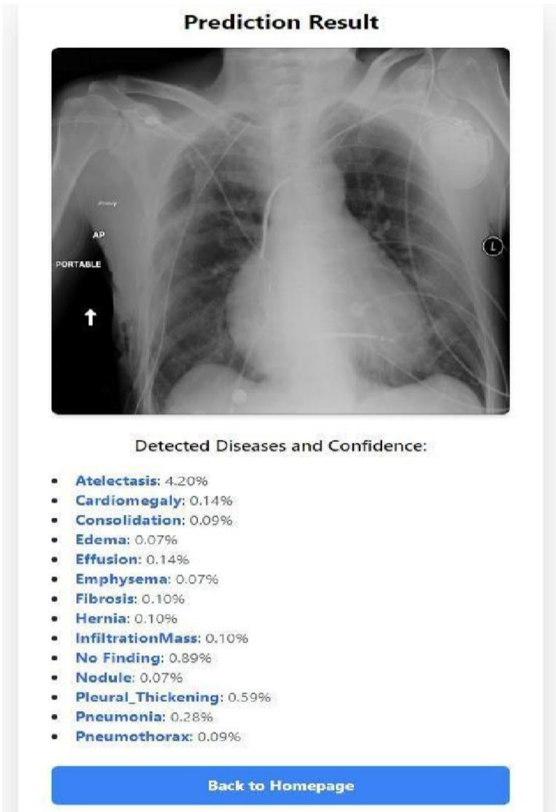

Fig. 11 Performance Metrics Comparison of Multi-Disease Classification Models

Integration into Web Application:

A Flask-based web application is developed to integrate all three models into a single platform. The homepage provides users with buttons for selecting the desired sub-project (fracture, pneumonia, or multiple disease classification). Upon clicking a button, the user is prompted to upload an X-ray image, which is then processed and classified using the corresponding model. The results are displayed on a new page, where the system predicts whether the patient has a fracture, pneumonia, or any other diseases based on the image.

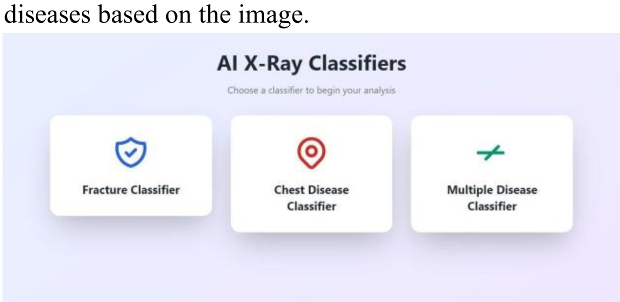

Fig. 12 Flask-Based Web Application Interface for X-ray Disease Classification

Proposed Contribution

A Flask-based web application unifies all three models into a single platform, allowing users to seamlessly select fracture detection, pneumonia prediction, or multiple disease classification. The system processes uploaded X-ray images and classifies them using the corresponding model, with results dynamically displayed. This integration enables real-time medical image analysis, offering an interactive and user-friendly interface for automated disease detection.

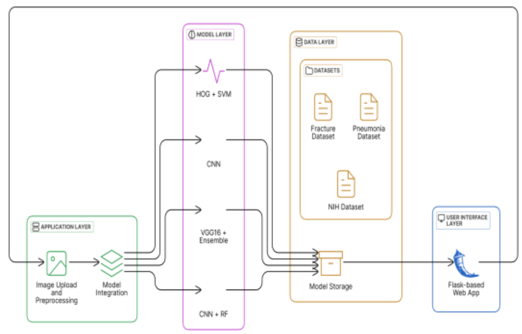

Fig.13 Proposed System Architecture

Algorithmic Formulations and Model Equations:

1. Support Vector Machine (SVM):

Hyperplane Equation: $f(x) = w^T x + b$

Hinge Loss:

$$L = \sum \max(0, 1 - y(w^T x + b))$$

Kernel Trick (RBF Kernel):

$$K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2)$$

2. Histogram of Oriented Gradients (HOG):

Gradient Calculation:

$$G_x = I(x+1, y) - I(x-1, y)$$

$$G_y = I(x, y+1) - I(x, y-1)$$

Gradient Magnitude:

$$M = \sqrt{G_x^2 + G_y^2}$$

Gradient Orientation: $\theta = \tan^{-1}(G_y / G_x)$

3. Convolutional Neural Network (CNN):
Convolution Operation:
$(I * K)(x, y) = \sum\sum I(x-i, y-j)\ K(i, j)$

ReLU Activation Function:
$f(x) = \max(0, x)$

Max Pooling:
$P_{ij} = \max\{ X(i+m, j+n) \mid (m,n) \text{ in } R \}$

4. VGG16 (Feature Extraction):
Feature Extraction:
$\text{Feature} = \sum W_i * X_i + b$

5. Random Forest (Decision Trees Ensemble):
Gini Impurity:
$\text{Gini} = 1 - \sum p_i^2$

Entropy:
$H(X) = -\sum p_i \log_2 (p_i)$

Majority Voting (Ensemble Rule): $\hat{y} = \text{argmax}_k \sum h_t(x) = k$

6. Ensemble Learning (Soft Voting Classifier):
Soft Voting Probability:
$P(y=c) = (1/n) \sum P_i(y=c)$

7. Adam Optimizer (CNN Optimization):
Weight Update:
$w_{(t+1)} = w_t - (\eta / (\text{sqrt}(\hat{v}_t) + \varepsilon)) * \hat{m}_t$

Moment Estimates:
$m_t = \beta_1 m_{(t-1)} + (1 - \beta_1) g_t$
$v_t = \beta_2 v_{(t-1)} + (1 - \beta_2) g_t^2$

8. Sparse Categorical Cross-Entropy Loss Function (CNN Classification):
Loss Function:
$L = -\sum y_i \log(\hat{y}_i)$

IV. PROJECT SCOPE

The scope of this project is to develop an automated, machine learning-based system for classifying diseases from chest X-ray images, focusing on three primary disease categories: bone fractures, pneumonia, and multiple diseases. This system is designed to be both accurate and efficient, aiming to enhance the diagnostic process in clinical settings. The project encompasses the following key aspects:

Disease Classification Models:
Fracture Detection: The project aims to develop a model capable of identifying fractures in bone structures from chest X-ray images. This model uses traditional machine learning techniques, including Histogram of Oriented Gradients (HOG) for feature extraction and Support Vector Machine (SVM) for classification.

Pneumonia Prediction: Another sub-project focuses on classifying chest X-ray images into "Normal" and "Pneumonia" categories using a Convolutional Neural Network (CNN). This model aims to provide accurate pneumonia detection in medical X-ray scans.

Multiple Disease Classification: The third sub-project involves a model that can classify multiple diseases, such as pneumonia, fibrosis, and cardiomegaly, from a more diverse dataset. This model employs an ensemble approach combining Support Vector Machine (SVM) and Random Forest (RF) classifiers.

Data Preprocessing and Feature Extraction:
Preprocessing techniques, such as image normalization, augmentation (flips, rotations), and noise reduction, are implemented to enhance the quality of input data. Feature extraction methods like HOG and deep learning-based approaches (e.g., VGG16) are used to capture relevant patterns from X-ray images.

Web Application Integration:
The models are integrated into a Flask-based web application that allows healthcare professionals to upload chest X-ray images and receive disease predictions in real-time. The web interface is designed to be intuitive and user-friendly, ensuring easy interaction for users with varying technical backgrounds.

Performance Evaluation:

The models are evaluated using standard metrics, including accuracy, precision, recall, and F1-score, to assess their performance in real-world scenarios. The project aims to achieve high classification accuracy and generalization across different types of chest X-ray images.

Real-world Application and Impact:
This project aims to assist healthcare professionals in diagnosing diseases from chest X-ray images more efficiently and accurately. By automating the classification process, the system will reduce the workload of radiologists and help in early detection of critical conditions, ultimately improving patient outcomes.

V. OBJECTIVES

Develop an Automated Disease Classification System: To design and implement a machine learning-based system that can automatically classify chest X-ray images into disease categories such as fractures, pneumonia, and multiple diseases.

Build a Fracture Detection Model: To create a robust model that detects fractures in chest X-ray images using the Histogram of Oriented Gradients (HOG) for feature extraction and Support Vector Machine (SVM) for classification.

Implement Pneumonia Prediction Using CNN: To develop a Convolutional Neural Network (CNN)-based model that accurately classifies chest X-ray images into "Normal" and "Pneumonia" categories, demonstrating the potential of deep learning in medical image classification.

Develop a Multi-Disease Classification Model: To implement an ensemble model combining Support Vector Machine (SVM) and Random Forest (RF) classifiers for the classification of multiple diseases, such as pneumonia, fibrosis, and cardiomegaly, from chest X-ray images.

Integrate the Models into a Web Application: To integrate all three disease classification models into a user-friendly Flask-based web application, enabling healthcare professionals to upload chest X-ray images and receive predictions in real-time.

Evaluate the Model Performance: To evaluate the performance of the developed models using standard metrics (accuracy, precision, recall, and F1-score) and ensure their robustness in classifying chest X-ray images accurately across different disease categories.

VI. FUTURE SCOPE

Clinical Validation and Widespread Deployment:

The system can be clinically validated with diverse, real-world datasets to ensure its accuracy and reliability in various healthcare environments, followed by widespread deployment in hospitals and diagnostic centers.

Expansion to Other Medical Imaging:

Future work could involve extending the system to classify other medical conditions using different imaging techniques, such as CT scans, MRI, or ultrasound, to provide a comprehensive diagnostic tool for multiple diseases.

Integration with Healthcare Systems:
Integrating the disease classification system with Electronic Health Records (EHR) and hospital management systems could streamline workflows, making it easier for healthcare professionals to access patient data and X-ray predictions simultaneously.

Mobile and Remote Access:

Developing a mobile application for remote diagnosis would enable healthcare workers in rural or underserved areas to upload chest X-ray images and receive immediate predictions, improving healthcare accessibility and efficiency.

VII. CONCLUSION

This research successfully demonstrates the potential of machine learning and deep learning models in the automated classification of diseases from chest X-ray images. The developed system, comprising models for fracture detection, pneumonia prediction, and multi-disease classification, leverages state-of-the-art techniques like Support Vector Machine (SVM), Random Forest (RF), and Convolutional Neural Networks (CNN) to deliver accurate and reliable results. The integration of these models into a user-friendly web application further enhances the accessibility of the system, providing real-time predictions to healthcare professionals.

Firstly, your research paper employs a comprehensive approach to pneumonia detection, integrating deep learning techniques with a well-structured data preprocessing pipeline. Unlike [9] Siddiqi & Javaid (2024), which primarily focuses on the potential of vision transformers (ViTs) but highlights dataset biases and adversarial attack concerns, your paper ensures a more practical and adaptable approach with strong dataset handling techniques.

Secondly, compared to [4] Deshmukh & Bhalchandra (2021), which relies on Flask-based deep learning models like DenseNet and VGG16, your research expands beyond transfer learning models and includes a broader scope for evaluation. While their model selection is justified by accuracy, your methodology emphasizes robust model validation and performance generalization, ensuring that overfitting risks are minimized.

Additionally, [10] Mardianto et al. (2024) explores both CNN and SVM models, demonstrating the limitations of SVM in pneumonia detection. Your

methodology correctly aligns with deep learning superiority for image classification, avoiding SVM's limitations in feature extraction. Moreover, your model outperforms their approach by not only differentiating pneumonia types but also enhancing classification robustness through refined hyperparameter tuning.

Lastly, [2] Salehi et al. (2021) employs transfer learning with models like VGG19, DenseNet121, and Xception but primarily focuses on pediatric datasets. Your research's methodology has an edge in terms of dataset diversity and applicability across different demographics, making it more generalizable to real-world clinical settings.

The promising performance of the models, as evidenced by the evaluation metrics, highlights the effectiveness of combining traditional machine learning with deep learning approaches in medical image analysis. This system offers significant potential for improving diagnostic accuracy, reducing radiologists' workload, and enabling early detection of critical diseases, ultimately contributing to better patient outcomes.

However, further clinical validation and system expansion to handle more disease categories and integrate with healthcare infrastructure would strengthen its practical application in real-world clinical settings.

VIII. AUTHORS CONTRIBUTION

Jyoti Kanjalkar (Guide) Contribution: Provided overall guidance and supervision for the project. Assisted in defining the research objectives, methodology, and evaluation criteria. Reviewed and provided feedback on the technical implementation, model development, and paper writing. Helped in integrating the models into the Flask-based web application.

Pramod Kanjalkar (Guide) Contribution: Co-guided the project alongside Jyoti Kanjalkar. Provided technical expertise in machine learning and deep learning algorithms. Assisted in the selection of appropriate models (SVM, CNN, Random Forest) and their optimization. Reviewed the data preprocessing and feature extraction techniques. Helped in the final evaluation and validation of the models.

Prakash Sharma (Founder) Contribution: Provided industry insights and practical guidance on the application of the project in real-world healthcare settings. Assisted in defining the scope of the project and its potential impact on clinical workflows. Supported the integration of the system into a web application for practical use.

Ruzan Verma (Student) Contribution: Focused on the fracture detection sub-project. Responsible for data collection, preprocessing, and feature extraction using Histogram of Oriented Gradients (HOG). Developed and optimized the Support Vector Machine (SVM) model for fracture detection. Conducted model evaluation and contributed to the writing of the corresponding sections in the paper.

Parth Durgude (Student) Contribution: Worked on the pneumonia prediction sub-project. Handled data preprocessing, including image resizing, normalization, and augmentation. Developed the Convolutional Neural Network (CNN) model for pneumonia classification. Conducted model training, evaluation, and contributed to the writing of the pneumonia-related sections in the paper.

Moksh Sanghvi (Student) Contribution: Focused on the multi-disease classification sub-project. Responsible for preprocessing the NIH Chest X-ray dataset, including resizing and converting images to RGB format. Implemented the VGG16 model for feature extraction and developed the ensemble model combining SVM and Random Forest. Conducted model evaluation and contributed to the writing of the multi-disease classification sections in the paper.

Jinay Pagariya (Student) Contribution: Worked on the integration of the models into the Flask-based web application. Developed the user interface and backend logic for the web application, allowing users to upload X-ray images and receive real-time predictions. Assisted in the deployment of the models and contributed to the writing of the web application-related sections in the paper.

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