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AI Based Bone Anomaly Detection Using Radiographic Data

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***Abstract*—This paper explores the use of ensemble learning techniques to detect bone anomalies from radiographic images in the MURA dataset, which contains 40,000 images of seven anatomical regions: wrist, fingers, humerus, hand, shoulder, forearm, and elbow. The study evaluates the accuracy and efficiency of an ensemble model combining AlexNet and ResNet architectures, trained on an 80:20 split of the dataset. Unlike existing approaches that utilize individual CNN models such as AlexNet, ResNet, or DenseNet with accuracies ranging from 85-90%, the proposed ensemble method achieved a superior accuracy of 95%. The model predicts whether a radiographic image contains an anomaly, demonstrating enhanced precision and robustness compared to standalone models. These results highlight the potential of ensemble learning for improving early detection and clinical decision-making, making it a promising tool for bone anomaly diagnostics in healthcare applications.**

***Index Terms*—Bone anomaly detection, ensemble learning, AlexNet, ResNet, MURA dataset, radiographic images, deep learning, healthcare AI, diagnostic accuracy.**

I. INTRODUCTION

The health and quality of life of patients are greatly impacted by bone abnormalities, such as fractures and other musculoskeletal conditions. Effective therapy and better patient outcomes depend on the early and precise diagnosis of these abnormalities. Radiographic imaging serves as a primary diagnostic tool; however, manual interpretation is often time-consuming and prone to errors, potentially leading to misdiagnoses and suboptimal treatment plans. Advancements in machine learning, particularly deep learning, have introduced automated methods to assist in the detection and classification of bone anomalies, aiming to enhance diagnostic accuracy and efficiency.

Current automated bone anomaly detection systems predominantly utilize individual convolutional neural network (CNN) architectures such as AlexNet, ResNet, and DenseNet. While these models have demonstrated commendable performance, achieving accuracies between 85% and 90%, they often encounter limitations in generalization and robustness when applied to diverse and complex datasets. Furthermore, depending only on one model architecture could limit the accuracy of diagnosis by failing to completely capture the complex patterns found in medical imaging data.

By utilizing ensemble learning strategies that integrate the advantages of several CNN architectures, this work seeks to improve the accuracy of bone anomaly identification. Specifically, the research focuses on developing an ensemble model integrating AlexNet and ResNet to improve diagnostic performance. The study involves training and evaluating this ensemble model using the MURA dataset, a comprehensive collection of musculoskeletal radiographs, to assess its effectiveness in detecting bone anomalies.

The scope of this research encompasses the utilization of the MURA dataset, which includes 40,561 labeled musculoskeletal radiographic images across seven anatomical categories: elbow, finger, forearm, hand, humerus, shoulder, and wrist. The study employs deep learning techniques, focusing on CNN architectures—AlexNet and ResNet—and their integration through ensemble learning methods. Evaluation metrics, including accuracy, precision, sensitivity, and specificity, are used to determine the effectiveness of the ensemble approach in bone anomaly detection. By addressing the limitations of existing single-model approaches, this study seeks to contribute to the development of more robust and accurate diagnostic tools in the field of medical imaging.

II. LITERATURE SURVEY

The paper [1] introduces a model for musculoskeletal abnormality detection using a combination of Lesion-

Guided Adaptive Graph Network (LGAG-Net), Lesion Region Feature Selection (LRFS) Module, Adaptive Graph Attention (AGA) Module, and Graph Convolutional Networks (GCN) for detecting musculoskeletal abnormalities from radiographs in the MURA dataset. This approach localizes abnormal regions using LRFS and enhances the detection within those areas via AGA, offering high accuracy and aiding radiologists by focusing on abnormal regions, reducing their workload. However, the model faces challenges in terms of high computational requirements and limited clinical applicability due to dataset constraints.

In order to identify anomalies in musculoskeletal radiographs from the MURA dataset, [2] employed Capsule Networks in an alternative technique. The study demonstrates the effectiveness of Capsule Networks in addressing issues of poor rotational invariance and spatial information loss. The model achieved a higher kappa score than DenseNet, with a 50% reduction in training data, making it especially useful for low-data scenarios. However, because of the intricate structure of the Capsule Networks, the method is computationally costly.

Another study in [3] explored the use of AlexNet, a Deep Convolutional Neural Network (DCNN), for classifying musculoskeletal X-ray images from the MURA dataset. This approach leveraged techniques such as image preprocessing (noise removal, color transformation), data augmentation, and AlexNet's architecture for feature extraction and classification. The method achieved an impressive classification accuracy of 95%, outpacing traditional machine learning methods. However, the model's dependence on substantial computational resources and risk of overfitting due to dataset dependency were identified as limitations.

The study in [4] presented a method for detecting bone anomalies using DenseNet-169 architecture on the MURA dataset. The model utilized image augmentation techniques like region of interest (RoI) detection, image cropping, and random transformations such as rotation, scaling, and brightness adjustments to enhance performance. Despite its high accuracy, challenges such as standardizing image quality across hospitals and managing low-resolution X-rays limit its practical use.

In [5], a DenseNet-based approach was proposed to detect bone abnormalities across various bone types, achieving an accuracy of 85%. Despite its success in handling data extraction and distinguishing normal from abnormal images, the model's performance is heavily dependent on dataset quality and the variation in image quality, which could impact its effectiveness in real-world scenarios.

The work in [6] explored the application of machine learning, specifically Ridge Regression and edge detection techniques, to identify bone fractures in X-ray images. The model used tools like TensorFlow, Scikit-Learn, OpenCV, and NumPy to enhance image quality and fracture visibility, with Ridge Regression further improving prediction accuracy by handling noisy data. However, the system is limited by the dependency on high-quality X-ray images and requires extensive preprocessing to identify minor fractures, as well as a large, diversified dataset for training.

The study in [7] presented the use of the Xception deep learning model to enhance the classification of upper bone abnormalities in X-ray images. Despite achieving higher efficiency and reliability in medical assessments, the model's training on large datasets can be time-consuming, and it is limited by a binary classification system that focuses only on specific upper bones, thus not covering the full range of bone abnormalities.

Finally, [8] utilized the VGG16 model for bone anomaly detection, significantly reducing diagnosis time compared to advanced imaging techniques like MRIs. However, the model's performance is sensitive to the quality of the dataset, as poor-quality X-rays or incomplete data can degrade the accuracy of predictions.

In [9], Region of Interest (ROI) extraction techniques were employed to focus on relevant bone areas, such as the wrist and fingers, for anomaly detection. The model used ensemble learning to combine the predictions of multiple CNN models, enhancing classification reliability. However, the model's accuracy depends on the correct extraction of ROI, and errors in ROI extraction can negatively impact model performance, leading to missed anomalies if key areas are excluded.

III. PROPOSED MODEL

The proposed method focuses on enhancing the accuracy of bone anomaly detection in radiographic images by utilizing a hybrid architecture that combines AlexNet and ResNet50. Initially, the MURA dataset, containing 40,000 radiographic images, is collected and preprocessed. Preprocessing steps include resizing the images to 256x256, normalizing pixel values, and applying data augmentation techniques such as rotation, flipping, and zooming to improve the generalization capability of the model.

The feature extraction process involves two architectures. AlexNet is used to extract local features through its convolutional and pooling layers, followed by global average pooling. ResNet50, pretrained on the ImageNet dataset, is employed to capture deep hierarchical features using its residual blocks and global average pooling. The features extracted from these architectures are then fused by concatenation, creating a comprehensive feature representation of the input image.

For classification, a dense neural network is added after the feature fusion. This includes fully connected layers with ReLU activation, dropout for regularization, and an output layer with a sigmoid activation function to classify the input as anomalous or normal. The Adam optimizer is used to train the hybrid model using a binary cross-entropy loss function and a learning rate of 0.001. Class weights are applied to address data imbalance, while early stopping and learning rate reduction techniques ensure efficient and optimized training.

The model is evaluated on unseen validation data using metrics like accuracy and AUC, along with its ability to correctly classify anomalies across different hand parts. By combining the strengths of AlexNet and ResNet50, the proposed method leverages local and global feature extraction, offering a robust and accurate solution for automated bone anomaly detection in medical diagnostics

IV. METHODOLOGY

Accurate bone anomaly detection in radiographic images is essential for medical diagnostics. To improve detection accuracy, this work uses a hybrid deep learning model that combines AlexNet and ResNet50. The MURA dataset undergoes preprocessing, including resizing, normalization, and augmentation (rotation, flipping, zooming) to improve data quality and model generalization. AlexNet extracts local features, while ResNet50 captures deep hierarchical features, with outputs fused for a comprehensive representation. The model is trained with techniques like class weighting to address imbalances and early stopping for efficient learning. Evaluation metrics such as accuracy and AUC validate the model's reliability in identifying anomalies. This approach ensures a robust and accurate solution for automated anomaly detection.

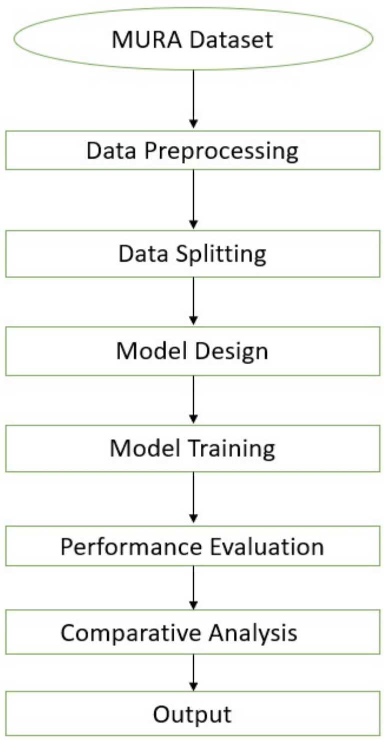

Fig 1: Flow of Methodology

A. Dataset Preparation

To increase variety, images were scaled, adjusted, and enhanced utilizing flipping, zooming, and rotation. These steps ensured consistency and improved model generalization. Data augmentation helped simulate real-world scenarios, making the model more robust. The preprocessed dataset served as the input for training and evaluation.

B. Data Splitting

Training (80%) and test (20%) sets of the dataset were separated to ensure a fair evaluation. Stratified splitting was used to maintain class balance across subsets. This ensured that all classes were proportionately represented in each split. The test set was saved for the model's final evaluation.

C. Model Design

A hybrid model was designed by combining AlexNet and ResNet50 architectures to leverage their complementary strengths. Feature vectors from both networks were merged and passed through a dense classifier head. Dropout regularization was applied to prevent overfitting. The model design aimed to extract both shallow and deep features for improved classification.

D. Training Procedure

By using the Adam optimizer to train the model at a learning rate of 0.001, effective convergence was guaranteed. A batch size of 32 was used for training throughout 25 epochs. When validation loss ceased getting better, training was halted early. Model convergence was improved by dynamically adjusting the learning rate through learning rate scheduling.

E. Performance Evaluation

The accuracy, precision, recall, and F1-score of the model were used to assess its performance on the hold-out test set. Confusion matrices and precision-recall curves were used to visualize the results. These measurements offered a thorough comprehension of the model's functionality. Evaluation helped identify strengths and weaknesses in predictions.

F. Comparative Analysis

The hybrid model was compared with ResNet152V2 and MobileNetV2 to benchmark its performance. The hybrid model achieved superior accuracy and a better balance of precision and recall. Comparative analysis demonstrated the effectiveness of combining AlexNet and ResNet50. This analysis validated the hybrid model as the final choice for deployment.

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