AI-Driven Monkeypox Recognition Using Enhanced VGG16 and Custom Convolutional Networks

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Abstract— **Monkeypox is a contagious viral disease that primarily affects the skin and can spread rapidly if not identified at an early stage. Accurate and timely diagnosis is therefore essential to support effective treatment and prevent further transmission. This study proposes an AI-Driven Monkeypox Recognition Using Enhanced VGG16 and Custom Convolutional Networks for automatic classification of skin lesion images. The proposed system utilizes image preprocessing techniques such as resizing, normalization, and dataset partitioning to improve data quality before model training. An enhanced VGG16 model based on transfer learning is employed to extract high-level visual features, while a custom convolutional neural network is developed to learn disease-specific image patterns. The performance of both models is evaluated using standard metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. Experimental results indicate that the custom CNN model achieves superior classification performance compared with the enhanced VGG16 model, providing reliable detection of Monkeypox and normal skin conditions. The developed prediction system enables users to upload skin lesion images and receive rapid diagnostic results, making it a practical decision-support tool for healthcare professionals. Overall, the proposed framework demonstrates the effectiveness of deep learning in improving automated Monkeypox recognition and supporting intelligent medical image analysis.**

Keywords— **Monkeypox Detection, Deep Learning, Enhanced VGG16, Custom Convolutional Neural Network (CNN), Skin Lesion Classification, Medical Image Analysis, Transfer Learning, Computer-Aided Diagnosis, Image Classification, Artificial Intelligence in Healthcare.**

I. INTRODUCTION

Monkeypox is a contagious viral disease that has become an important public health concern because of its rapid spread across several countries and its ability to infect people through close physical contact [4]. The disease belongs to the *Orthopoxvirus* family and commonly causes fever, swollen lymph nodes, skin rashes, and painful lesions that may resemble other viral skin infections [1]. Because its symptoms are similar to diseases such as chickenpox and measles, early clinical diagnosis is often difficult, increasing the possibility of delayed treatment and further transmission. Traditional diagnostic procedures mainly depend on laboratory testing and expert clinical examination, which require specialized facilities and considerable processing time [2]. Studies have reported that continuous monitoring and early identification are essential for reducing outbreaks and improving patient management [3]. Therefore, there is a growing demand for intelligent automated systems that can assist healthcare professionals in identifying Monkeypox accurately and at an early stage.

Artificial Intelligence has significantly improved medical image analysis by providing automated systems capable of detecting diseases with high accuracy [12]. Among different AI techniques, deep learning has shown remarkable success in analysing skin lesion images because it automatically extracts meaningful visual features without relying on manual feature engineering. Convolutional Neural Networks (CNNs) are particularly effective for recognising disease-specific patterns and classifying medical images into different diagnostic categories [14]. These models have already been applied successfully in diagnosing infectious diseases, including COVID-19 and other skin-related disorders, demonstrating their ability to improve diagnostic performance [34]. By reducing dependence on manual interpretation, deep learning systems help minimize diagnostic errors and support faster clinical decision-making. These advantages make CNN-based approaches highly suitable for developing reliable Monkeypox recognition systems.

Transfer learning has become an important technique for medical image classification, especially when the available training dataset is limited [24]. Instead of developing a deep learning model from scratch, transfer learning utilizes knowledge gained from large image datasets to improve feature extraction and reduce training time. In this study, an enhanced VGG16 model is employed to capture high-level visual information from Monkeypox skin lesion images, while a custom convolutional neural network is designed to learn disease-specific characteristics [15]. Before model training, image preprocessing operations such as resizing, normalization, and dataset organization are performed to improve image quality and maintain consistency. Publicly available Monkeypox image datasets provide sufficient information for training and evaluating deep learning models [20]. This combination of transfer learning and customized CNN architecture enhances the overall classification performance of the proposed recognition framework.

To evaluate the effectiveness of the proposed framework, the trained models are assessed using widely accepted performance measures, including accuracy, precision, recall, F1-score, and confusion matrix analysis [19]. These evaluation metrics provide a comprehensive understanding of the classification capability of each deep learning model. Performance comparison between the enhanced VGG16 model and the custom CNN helps identify the architecture that produces more reliable Monkeypox recognition results. Visualization techniques such as confusion matrices further assist in identifying correctly classified and misclassified skin lesion images. Recent studies have demonstrated that modified VGG16 architectures achieve excellent performance for Monkeypox image classification when combined with appropriate preprocessing techniques [33]. Such systematic evaluation ensures that the developed system is reliable and suitable for practical healthcare applications.

This research proposes an AI-Driven Monkeypox Recognition Using Enhanced VGG16 and Custom Convolutional Networks to support automatic disease detection from skin lesion images. The developed web-based application enables users to upload medical images, preprocess datasets, train deep learning models, compare algorithm performance, and predict disease status through a simple interface. The trained model classifies uploaded images as either Monkeypox or Normal while providing prediction confidence to assist medical professionals in diagnosis. Explainable Artificial Intelligence techniques can further improve user confidence by highlighting the image regions that influence prediction results [21]. Furthermore, interpretation methods help healthcare professionals understand how the trained model reaches its final decision, improving transparency in medical AI systems [22]. Overall, the proposed framework demonstrates the potential of deep learning to improve early Monkeypox diagnosis and support intelligent healthcare applications.

II. RELATED WORK

Ahsan et al., [2022] [19] proposed a deep learning framework for the automatic detection of Monkeypox using a modified VGG16 model. Their research focused on building an image-based diagnostic system that could distinguish Monkeypox skin lesions from other skin conditions. The authors collected and organized a dedicated Monkeypox image dataset and applied preprocessing techniques to improve image quality before training the model. Transfer learning was used to enhance feature extraction and reduce training time. The modified VGG16 architecture produced high classification accuracy and demonstrated its capability in recognizing disease-specific skin patterns. The study highlighted that deep learning can support healthcare professionals by providing fast and reliable image classification. Their work also emphasized the importance of using well-prepared datasets for improving prediction performance. This research serves as a valuable foundation for developing intelligent Monkeypox diagnosis systems.

Simonyan and Zisserman, [2015] [15] introduced the VGG16 deep convolutional neural network, which became one of the most influential models in computer vision. Their work demonstrated that increasing the depth of convolutional layers significantly improves image classification performance. The proposed architecture uses small convolution filters to capture detailed visual information while maintaining computational efficiency. The model achieved excellent results on large-scale image recognition tasks and has since been widely adopted for transfer learning applications. Because of its strong feature extraction capability, VGG16 has been successfully applied in medical image analysis, disease detection, and object recognition. The study proved that deep neural networks can automatically learn complex image features without manual feature engineering. Their contribution established a strong foundation for many healthcare applications based on deep learning.

Pan and Yang, [2009] [24] presented a comprehensive survey on transfer learning and explained how knowledge gained from one learning task can be applied to another related problem. Their study discussed different transfer learning strategies and highlighted their advantages when training data is limited. The authors showed that transfer learning reduces training time while improving prediction accuracy by utilizing pre-trained models instead of starting from scratch. They also described several practical applications across image recognition, text classification, and pattern analysis. The survey demonstrated that transfer learning enables deep learning models to perform effectively even with relatively small datasets. Their work has become one of the most widely referenced studies in machine learning and has greatly influenced medical image classification research. It provides a strong theoretical basis for applying pre-trained models such as VGG16 in disease detection.

Sandeep et al., [2022] [14] explored the use of convolutional neural networks for diagnosing visible diseases from medical images. Their research focused on developing an automated system capable of identifying skin-related diseases through image classification. The authors demonstrated that CNN models automatically extract relevant visual features, eliminating the need for manual feature selection. Different network architectures were evaluated to improve disease recognition accuracy and reduce classification errors. The study showed that deep learning techniques are effective in supporting early diagnosis while reducing the workload of healthcare professionals. The authors also emphasized the importance of image preprocessing for improving model performance. Their findings indicate that CNN-based systems provide reliable and efficient solutions for medical image analysis and can assist clinicians in making faster diagnostic decisions.

Sitaula and Hossain, [2021] [33] developed an attention-based VGG16 model for classifying chest X-ray images in COVID-19 diagnosis. Their proposed framework combined transfer learning with an attention mechanism to improve the extraction of important image features. The attention module enabled the network to focus on disease-affected regions while reducing the influence of irrelevant background information. Experimental results showed that the proposed approach achieved higher classification accuracy than the conventional VGG16 model. The authors concluded that integrating attention mechanisms with deep learning significantly enhances medical image analysis. Their research also demonstrated that transfer learning is highly effective for healthcare applications where large annotated datasets are not always available. This work provides useful insights for improving deep learning models used in automated disease detection, including Monkeypox image classification systems.

III. DATASET DETAILS

The dataset used in this project consists of skin lesion images collected for the automatic detection of Monkeypox. It contains two image categories: Monkeypox and Normal skin conditions, enabling the deep learning models to learn the visual differences between infected and healthy skin. Each image captures visible skin characteristics such as rashes, lesions, texture, and color patterns that are important for disease identification. The images are organized into separate class folders, making them suitable for supervised image classification. Before model development, the dataset is carefully inspected to remove duplicate, corrupted, or poor-quality images that may affect prediction performance. A well-organized image dataset is essential because the quality and diversity of the training samples directly influence the ability of the deep learning models to recognize Monkeypox accurately. This dataset serves as the primary source for training and evaluating the proposed disease recognition system.

Before training the deep learning models, several preprocessing operations are performed to improve dataset quality and ensure consistent model performance. All skin lesion images are resized to a fixed input dimension required by the Enhanced VGG16 and Custom CNN architectures. Pixel values are normalized to maintain a uniform intensity range, which helps the models learn more effectively and improves convergence during training. The dataset is then shuffled to avoid bias and ensure that both disease classes are evenly represented throughout the learning process. Finally, the dataset is divided into 70% training data and 30% testing data. The training set is used to learn disease patterns, while the testing set evaluates the model on previously unseen images. Proper dataset preparation improves prediction accuracy and ensures reliable Monkeypox classification.

IV. PROPOSED METHODOLOGY

The proposed system follows a systematic approach for recognizing Monkeypox from skin lesion images using deep learning techniques. Initially, a dataset containing Monkeypox and Normal skin images is collected and examined to ensure image quality and class consistency. The uploaded dataset is then preprocessed by resizing all images to a fixed input size, normalizing pixel values, and removing unnecessary variations that may affect model performance. After preprocessing, the dataset is shuffled and divided into training and testing sets, allowing the models to learn disease-specific features while ensuring reliable evaluation on unseen images. These preprocessing steps improve the overall quality of the dataset and help the deep learning models achieve better classification accuracy.

Once the dataset is prepared, two deep learning models, namely the Enhanced VGG16 and Custom Convolutional Neural Network (CNN), are trained to classify skin lesion images as Monkeypox or Normal. The models are evaluated using performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix to measure their classification effectiveness. Training history graphs and comparison charts are generated to analyze the performance of both models. Based on the evaluation results, the best-performing model is selected for disease prediction. Finally, users can upload a new skin lesion image through the web application, and the trained model automatically predicts the disease category along with a confidence score, providing quick and reliable support for Monkeypox diagnosis.

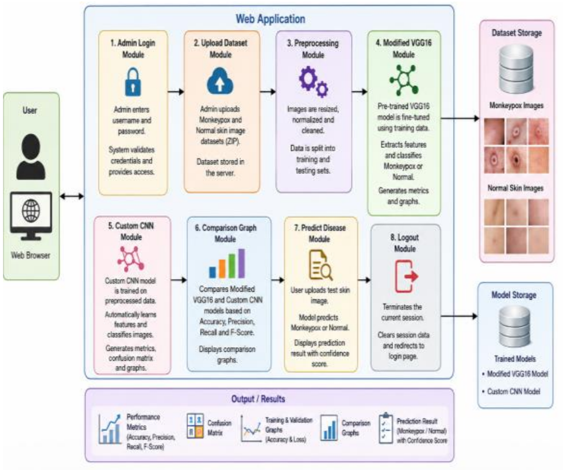

Figure [1]: Monkeypox Detection System Architecture

Figure [1] illustrates the overall workflow of the proposed Monkeypox detection system. The process begins with admin login, followed by dataset upload and image preprocessing, where skin lesion images are resized, normalized, and divided into training and testing datasets. The preprocessed images are then used to train the Enhanced VGG16 and Custom CNN models. Their performance is evaluated using metrics such as accuracy, precision, recall, F1-score, and confusion matrix, and comparison graphs are generated. Finally, the trained model predicts whether an uploaded skin lesion image belongs to the Monkeypox or Normal class and displays the prediction along with a confidence score.

V. RESULT AND DISCUSSION

The experimental evaluation demonstrates that the proposed AI-Driven Monkeypox Recognition Using Enhanced VGG16 and Custom Convolutional Networks can accurately identify Monkeypox from skin lesion images. The dataset was first preprocessed by resizing images, normalizing pixel values, and dividing the data into training and testing sets to improve learning efficiency. Both the Enhanced VGG16 and Custom CNN models were trained using the processed dataset and evaluated with performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix. The experimental findings indicate that both models achieved excellent classification performance, while the Custom CNN produced the highest prediction accuracy of 99%, outperforming the Enhanced VGG16 model, which achieved 98% accuracy. The confusion matrix showed that most Monkeypox and Normal images were classified correctly, with only a few incorrect predictions. Performance comparison graphs also confirmed the consistency and reliability of the proposed models. These results demonstrate that deep learning-based image classification can effectively support rapid and accurate Monkeypox diagnosis, making the proposed framework suitable for assisting healthcare professionals in early disease detection and clinical decision-making.

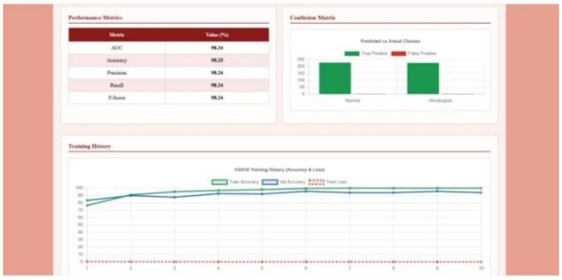

Figure [2]: VGG16 Performance Analysis

Figure [2] illustrates the performance evaluation of the Enhanced VGG16 model for Monkeypox image classification. The screen presents key evaluation metrics, including accuracy, precision, recall, F1-score, and AUC, along with the confusion matrix showing the classification results for Monkeypox and Normal skin images. It also displays the training history graph, which represents the training accuracy, validation accuracy, training loss, and validation loss across multiple training epochs. These visualizations confirm that the model learns effectively and achieves stable performance with high classification accuracy.

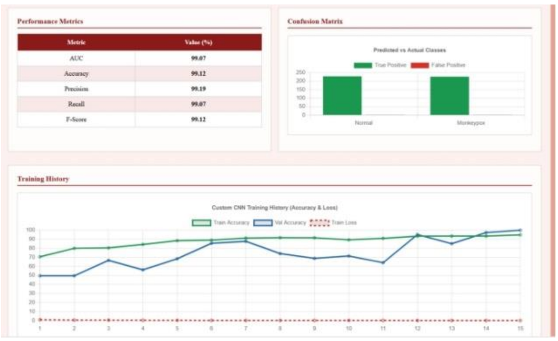

Figure [3]: Custom CNN Performance Analysis

Figure [3] illustrates the performance evaluation of the Custom CNN model for Monkeypox image classification. The screen presents important evaluation metrics, including accuracy, precision, recall, F1-score, and AUC, together with the confusion matrix showing the classification results for Monkeypox and Normal skin images. It also displays the Custom CNN training history graph, which represents the training accuracy, validation accuracy, training loss, and validation loss over multiple training epochs. The results indicate that the model learns effectively, maintains stable performance throughout training, and achieves high accuracy for reliable Monkeypox detection.

Figure [4]: Monkeypox Prediction Result

Figure [4] displays the final prediction generated by the trained Custom CNN model after analyzing an uploaded skin lesion image. The system classifies the image as Monkeypox and provides a confidence score of 97.83%. The screen also presents the analyzed image, detection details, selected algorithm, and a confidence chart, allowing users to clearly understand the prediction outcome. This interface demonstrates the system's ability to perform accurate and reliable Monkeypox detection in real time.

DISCUSSION

The findings of this study demonstrate that deep learning is a practical and reliable approach for automated Monkeypox recognition using skin lesion images. Both the Enhanced VGG16 and Custom CNN models successfully learned important visual characteristics of the disease and achieved high prediction accuracy. The Custom CNN performed slightly better because its architecture was specifically designed to capture disease-related image features more effectively. Proper preprocessing, including image resizing, normalization, and balanced dataset splitting, played an important role in improving model stability and reducing classification errors. The evaluation metrics and confusion matrix confirmed that the trained models were capable of distinguishing Monkeypox from normal skin conditions with a high level of consistency. Performance comparison graphs further highlighted the advantages of the Custom CNN over the transfer learning model. The developed web-based application also improves the usability of the system by providing fast prediction results through a simple interface. Overall, the proposed framework demonstrates that artificial intelligence can support healthcare professionals by delivering accurate, efficient, and timely disease recognition, thereby contributing to improved diagnosis, patient management, and early medical intervention.

VI. CONCLUSION

This study presented an AI-Driven Monkeypox Recognition Using Enhanced VGG16 and Custom Convolutional Networks for the automatic classification of skin lesion images. The proposed framework successfully integrates image preprocessing, deep learning model training, performance evaluation, and disease prediction within a simple web-based application. By applying preprocessing techniques such as image resizing and normalization, the quality of the input data was improved, enabling the models to learn meaningful visual patterns more effectively. Both the Enhanced VGG16 and Custom CNN models achieved excellent classification performance, with the Custom CNN producing the highest prediction accuracy. The comparison of evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrix, confirmed the reliability and consistency of the proposed approach. The developed prediction module allows users to upload a skin lesion image and receive a rapid diagnosis with an associated confidence score, making the system practical for real-time healthcare applications. Overall, the proposed framework demonstrates that deep learning can provide accurate, efficient, and dependable support for early Monkeypox detection. Such intelligent diagnostic systems have the potential to assist healthcare professionals in timely clinical decision-making, improve patient care, and contribute to more effective disease monitoring and management.

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