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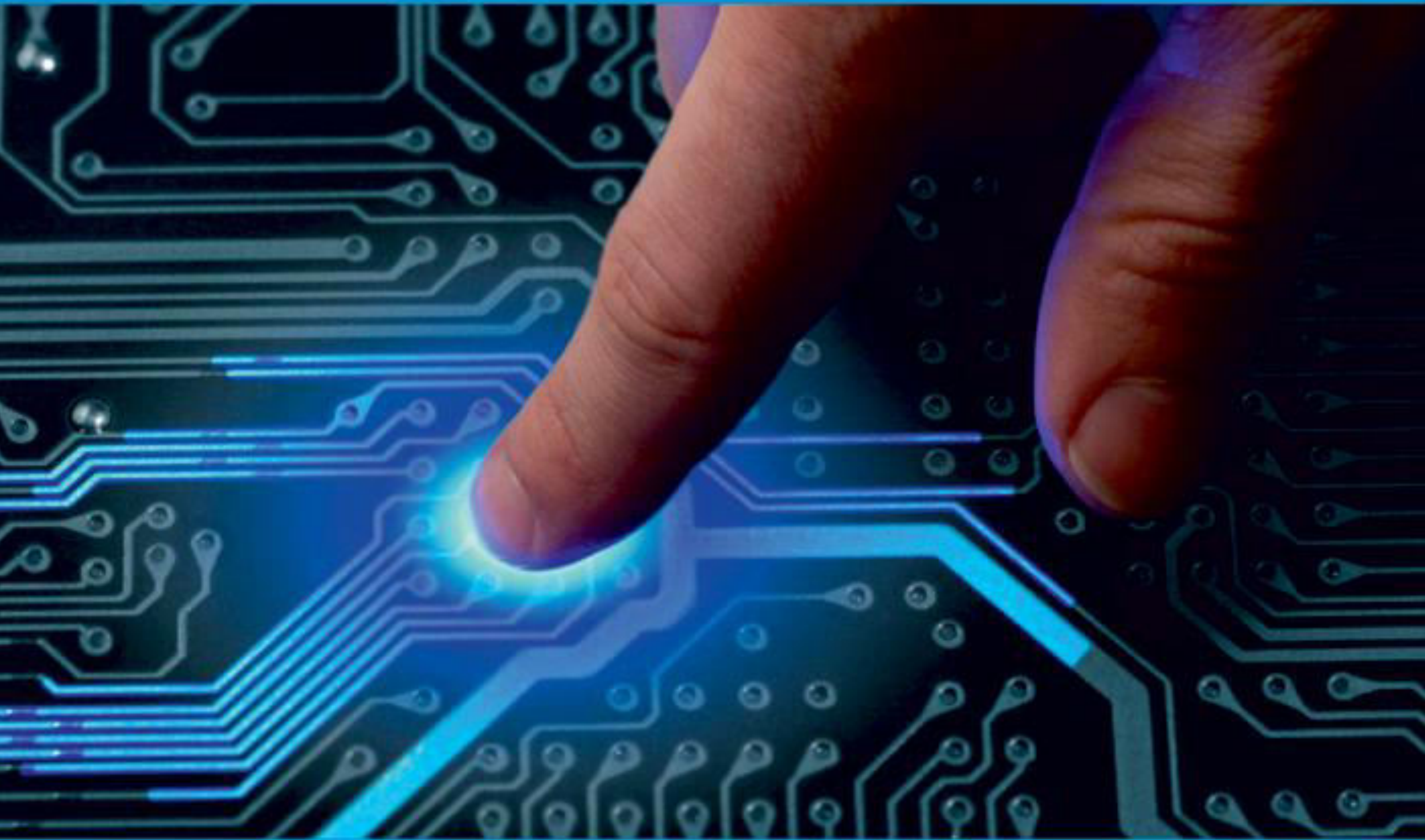

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Monkeypox Detection with Interpretable Deep Learning and Image Processing

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ABSTRACT: As the global community slowly recovered from the complications of COVID-19, the recent worldwide spread of the disease known as monkeypox has raised concerns about a potential pandemic. This emphasises how crucial early detection and treatments are to halting the disease's spread. A potential remedy is deep learning-based disease prediction, which provides accessible and reasonably priced diagnostic services. According to the research, monkeypox is a virus that represents a serious risk to public health, especially in areas where outbreaks are frequent. Effective disease administration and outbreak control of monkeypox depend on early and precise diagnosis. In this work, we propose a novel technique to monkeypox diagnosis using an understandable Deep Learning Convolutional Neural Network. Our program automatically detects and classifies monkeypox lesions using state-of-the-art deep neural network algorithms and a large database of clinical images. Crucially, the CNN algorithm gives clinicians comprehensible insights into the procedure for making choices, enabling them to comprehend the characteristics that influence the diagnosis.The suggested CNN model outperformed conventional machine learning techniques in the detection of monkeypox lesions, achieving an astounding 98.67% accuracy rate. Our suggested approach shows excellent accuracy and dependability in diagnosing monkeypox after thorough testing and validation, providing a potentially useful tool for medical practitioners to improve patient care and disease surveillance.

KEYWORDS: Monkeypox; Deep Learning; Convolutional Neural Network; Healthcare; Diagnosis

I. INTRODUCTION

The infectious agent known as the monkeypox virus, which is frequently present in monkeys, causes monkeypox[1][2].In the federal republic of Congo, monkeypox reappeared in 2014 after being first discovered in 1958[3]. Although it is not as well-known as Zika or Ebola, it has the potential to become a serious worldwide health issue[4].The World Health Organisation has declared an international health emergency due to the monkeypox outbreak[5].There are more and more instances recorded every day, indicating that it is still spreading[6].The number of instances reported increased in the west Pacific, European, and American regions in the two weeks preceding August 9, 2023[7]. Because of its dermatological symptoms, which closely match those of several different illnesses, monkeypox is difficult to diagnose clinically[8]. Usually, the illness starts as a rash and develops into pustules and scabs. Before extending to other areas of the body, the outbreak is typically most noticeable on the face[9].Chickenpox, another illness characterised by an itchy, vesicle rash which develops into fluid-filled lesions and eventually scabs, presents similarly to this[10]. On the other hand, chickenpox rashes typically cover a larger area of the body[11].Furthermore, measles, a communicable illness marked by a red, mottled rash, can be mistaken for monkeypox in its early stages. The measles rash begins on the face and moves downward, much like monkeypox[12]. Skin diseases like lupus and eczema that are not contagious make diagnosis even more difficult. Eczema can be confused with the initial phase of monkeypox because of its irritated, itchy skin patches.

Methods based on deep learning have recently gained popularity as an efficient way to analyse images and recognise patterns; they are especially helpful in diagnosing a variety of ailments. DL, a subfield of machine learning, extracts characteristics from images and performs predictive assessments by using numerous levels of artificial neural network

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structures. Many medical imaging applications have successfully used Convolutional Neural Networks, a DL method. These include lung nodule identification, breast cancer detection, and skin lesion classification.Promising answers to these problems can be found in automated systems that use machine learning along with deep learning[13]. Different convolutional neural networks, or CNNs, showed efficacy in distinguishing between images of different disorders. This development suggests that diseases such as COVID-19, pneumonia, and thyroid carcinoma can now be detected on their own without a physician's direct assistance. The use of DL becoming even more important when considering infectious disorders such as monkeypox.CNNs' capacity to identify patterns and characteristics in medical images presents a viable way to address the difficulties presented by illnesses that exhibit visual symptoms. By offering precise and effective illness detection, these automated systems, which depend on ML and DL, have an opportunity to revolutionise the diagnostic procedure. A bright future for autonomous diagnosis in medicine is suggested by CNNs' ability to distinguish between photos of various medical diseases.

This new development highlights how deep learning may be used to address public health issues, especially the detection of infectious illnesses like monkeypox. It is feasible to create reliable diagnostic tools that improve disease diagnosis accuracy and aid in quicker and more effective disease management by utilising the features of sophisticated CNNs[14]. However, using trained deep neural network techniques on edge devices is crucial for effective early identification of infectious illnesses like monkeypox.Given that this strategy offers several significant advantages, such as improved accessibility that enables its widespread application in a range of settings, including distant ones; the ability to respond quickly by giving prompt feedback on possible health issues; and the substantial relief it provides to healthcare providers by automating the early stages of disease recognition.This work's primary contributions are as follows:

- To automatically detect and classify monkeypox lesions, researchers suggest the use of convolutional neural networks. This model's accuracy and dependability in differentiating monkeypox from visually comparable illnesses like chickenpox, measles, & eczema are improved by training it on a sizable dataset of labelled clinical images.
- The CNN model is designed to be interpretable, providing insights into the diagnostic process. This interpretability allows clinicians to understand the features and patterns influencing the model's diagnosis, fostering trust and transparency in AI-driven healthcare tools.
- By enabling rapid, non-invasive diagnosis, this CNN-based approach is particularly beneficial for regions with limited healthcare infrastructure. The system offers a scalable solution that can be deployed on edge devices, facilitating early disease detection.
- This work addresses the limitations of manual diagnostic methods that are often time-consuming and error-prone. Our automated system provides high accuracy, minimizing the dependency on extensive laboratory testing and reducing diagnostic delays.

The following is the arrangement of the remaining sections: Section II presents a review of previous studies, Section III explains the proposed methodology, Section IV displays the findings and solutions, & Section V concludes the findings of the research.

II. RELATED WORKS

Raha et al. [15]addressed by using deep learning models on edge devices, which offer a practical way to quickly and precisely detect monkeypox. Lightweight deep learning models must be used, though, due to the resource limitations of edge devices. In the context of medical diagnostics, the accuracy trade-off that these models frequently entail is unacceptable. Consequently, For edge computing, developing deep learning algorithms that are both extremely accurate and efficient with resources becomes crucial.In order to do this, an attention-based MobileNetV2 framework for monkeypox identification is put forth, utilising MobileNetV2's built-in lightweight architecture for efficient deployment on edge devices. Researchers employed gradient-weighted class activation & local comprehensible model-agnostic explanations Mappings to guarantee interpretability and transparency while offering distinct insights into the diagnostic justification of the model. This research outperformed the baseline mathematical models, achieving 92.28% accuracy within the MSID dataset that was expanded, 98.19% accuracy in the MSID dataset that was first created, and 93.33% accuracy in the MSLD dataset.

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Sitaula and Shahi[16] explains that With the global decrease in COVID-19 virus transmission, the monkeypox virus is gradually becoming more prevalent. People fear it because they believe it will manifest as a pandemic similar to COVID-19. Therefore, early detection is essential before extensive dissemination among the community. Early detection may be possible with AI-based detection. This is accomplished by first fine-tuning them through implementing universal custom layer for each one of them, and then evaluating the results using established metrics. After determining which DL models demonstrated the best performance, this paper use a majority vote over the probabilistic findings they provide to ensemble them in order to enhance overall performance. Using a publicly accessible dataset, this workconductsthe trials and, with the aid of our suggested ensemble technique, obtain mean.These encouraging results, which outperform the most cutting-edge methods, show that medical practitioners can employ the recommended approach for mass screening.

Five popular pretrained deep neural network algorithms were tested for performance and accuracy levels in mpox detection. The models' accuracy, recall, precision, & F1-score were among the criteria used to evaluate their performance. The MobileNetV2 network possessed the best categorisation outcomes for the trial data, with 98.16% proficiency in classification, 0.96 recall, 0.99 preciseness, as well as 0.98 F1 score[17].Additionally, the MobileNetV2 network demonstrated the highest accuracy, at 0.94%, when tested on a variety of databases. the findings show that the MobileNetV2 approach performs better in mpox photo classification than previous models reported in published investigations. In both sets of tests and training, the system demonstrated a high degree of mpox categorisation accuracy, which could make it a useful tool for prompt and precise diagnosis in clinical situations.

Uzun Ozsahin et al. [18]presents that impact human subjects, as DL-based algorithms have recently been viewed as an exciting possibility in the medical field. Two open-source digital skin pictures of chickenpox and monkeypox were used in this investigation. Four convolutional layers made up the two-dimensional convolutional deep neural network was used. The 2nd, 3rd, &4th convolutional layer layers were then followed by three MaxPooling layers. In comparison to other pre-trained models, the poorest while considering an accuracy rating of 80.00%.The recommended CNN model is generalised and prevents over-fitting because of its uniqueness and the image augmentation methods used. Using digitised skin pictures of individuals suspected of having monkeypox, this hypothetical scenario would be valuable for the rapid and exact diagnosis of the disease.

The recent outbreaks of monkeypox have raised concerns globally due to its rapid spread and the limitations in manual diagnostic procedures.Traditional methods for detecting monkeypox through clinical examination and laboratory testing are often time-consuming, resource-intensive, and prone to human error[18]. An automated, precise, and effective technique for the early identification and diagnostic of monkeypox utilising medical imaging is therefore desperately needed. Monkeypox can be identified from photos of skin lesions using a DL-based method that makes use of interpretable artificial neural networks and sophisticated image processing techniques. The system can correctly classify monkeypox lesions by training a model on a collection of annotated images, and interpretable models guarantee decision-making transparency. This method improves diagnostic accuracy by providing a quick, non-invasive, and scalable option, particularly in areas with restricted access to medical institutions.

III. MONKEYPOX DETECTION USING CONVOLUTION NEURAL NETWORK

The article presents a methodical approach to the precise digital representation and visualization of historical spots, monuments, and cultural artefacts. There are several processes involved in this process, starting with data collecting. The obtained data is then pre-processed to guarantee geometric correctness and completeness. It consists of noise reduction, alignment of point clouds, and reconstruction of meshes. Super positioning of high-resolution images at the surfaces of the antiquities is done after their generation in 3D. Texture mapping provides photographic richness and detail to the texture-mapped images. Comprehensive evaluation and validation processes occur at various stages of process against the quality, correctness, and aesthetics of the digital objects. The workflow of proposed framework is depicted in Fig. 1.

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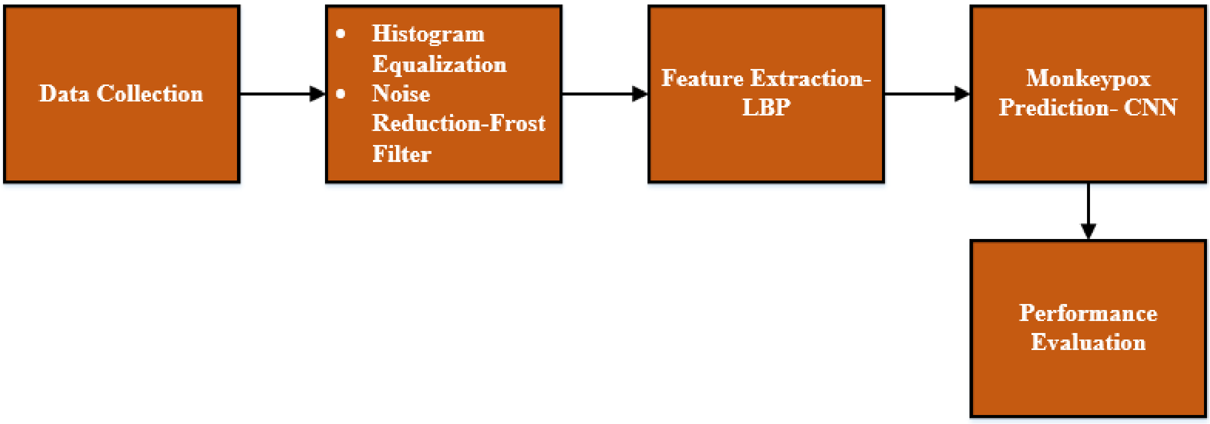

FIG 1Work flow of Proposed Methodology

A. Data Collection

DermNet and the Monkeypox Skin Images Data are two premium databases from which the dataset used in this work is derived. There are four image subgroups in MSID: measles, chickenpox, monkeypox, and normal conditions of the skin. These images have been collected from reliable online sources, which include health websites, newspapers, and scholarly journals. To add variety and richness to the dataset, pictures from the DermNet open repository were added, making the final count eight classes. For the monkeypox class, images are described as initially having a rash that later turns into pustules and scabs. Measles images depict a red, blotchy rash that is centered on the face and spreads down. Pictures of eczema depict inflamed, itchy patches of skin, which differ in appearance depending on the color of the skin but probably would look similar to the rashes associated with monkeypox to the naked eye[19]. The data is massive and diversified to support deep learning models in robust training and evaluation procedures of accurate classification of skin disease and prediction of monkeypox[20].

B. Histogram Equalization and Noise Reduction Using Frost Filter

1. Histogram Equalization: In medical imaging preprocessing, Histogram Equalization and Noise Reduction are essential techniques because they lead to the enhancement of image quality and diagnostic accuracy through the sharpness obtained in images, especially through deep learning. Contrast enhancement of medical images is achieved by redistributing intensity values through the use of Histogram Equalization to obtain an image where the contrast between two different regions, such as a lesion versus healthy skin, is enhanced. This alteration allows the CNN models to better identify minor patterns, especially so in images where a lighting or exposure variation may obscure important details.

2. Noise Reduction Using Frost Filter: Frost Filter is applied to Noise Reduction, a common process in medical imaging to remove speckle noise—the randomness in pixel intensity resulting from factors such as the presence of sensor artifacts or environment. the Frost Filter makes sure that the CNN model receives cleaner and clearer input data, which would then give results in terms of classification, more reliable than less accurate results. All of these preprocessing steps taken together are enhancing the robustness of the model and can lead to more consistent and interpretable deep learning results.The following is the expression for the frost filterwhich is depicted in (1).

$$F_f = \sum_{n\times n} K\alpha e^{-\alpha|t|} \quad (1)$$

$$\alpha = \left(\frac{4}{n\sigma^{-2}}\right)\left(\frac{\sigma^2}{\bar{I}^2}\right) \quad (2)$$

Where,"K" stands for normalised constant, $\bar{I}$for local mean, and "σ for local variance". The fluctuation of image coefficient is denoted as $\bar{\sigma}$, and "n is the moving kernel size".

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C. Feature Extraction Using Local Binary Patterns

Local Binary Patterns is actually a very powerful feature extraction method to capture texture features in medical images particularly useful for skin lesion differentiation in the monkeypox diagnosis. LBP actually encodes the texture pattern through the conversion of local intensity differences into a binary code with the aid of the comparison of each pixel's intensity with neighbors. The LBP, assigns the value of 1 or 0 to every pixel. In other words, if the neighboring pixel has a high intensity, then the value is 1, when it's low then it's 0, and then from this binary pattern, which reflects the local texture, a histogram representing the distribution of textures in the image is obtained.The expression for Local binary pattern is given in (3),

$$\mathrm{LBP}_{p,r}(X_c) = \sum_{p=0}^{p-1} \mu(X_p - X_C) 2^p, \mu(z) = \begin{cases} 1, z \geq 0 \\ 0, z < 0 \end{cases} \quad (3)$$

Due to its texture properties, monkeypox lesions are particularly good for pattern extraction; therefore, it offers robust and interpretable features for the improvement in machine learning models towards the detection of the disease. For this sensitivity to a subtle texture that LBP presents, it makes it suitable for the construction of proper and reliable prediction models aimed at early detection and differentiation of monkeypox lesions from other skin conditions.

D. Monkeypox Prediction Using Convolution Neural Network

It attempts to mechanically learn and identify any specific patterns in medical photos related to the diagnosing of monkeypox by utilizing the authority of deep learning, thus providing an accurate and efficient approach. CNN is designed particularly for image analysis due to spatial hierarchies and complicated textures of the images where features are learned through more than one layer.It uses a standard CNN, which includes "convolutional, pooling, and fully connected layers", as demonstrated in monkeypox prediction. Several filters are used to each convolutional layer's picture inputs for the purpose to extract characteristics. In each filter, the specific pattern learned actually corresponds to the relevant monkeypox, the distinctive texture, and shape of lesions. The operation in every convolutional layer can be represented as:

$$y_{i,j}^k = f\left(\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x_{i+m,j+n} \cdot w_{m,n}^k + b^k\right) \quad (4)$$

Where "$y_{i,j}^k$" is the output feature map at position "(i,j)" for filter "k","x" is the input image or the output of the previous layer,"$w_{m,n}^k$" represents the weights of the "k-th filter", b^k is the bias term, and "f" is the activation function, typically" ReLU (f(x)=max(0,x)".

Following the convolution layers of data, the characteristics maps' spatial dimensions are decreased by the pooling layers. This lowers the possibility of overfitting and increases the network's overall efficiency. Max pooling is the most commonly used pooling procedure, and it may be expressed as,

$$y_{i,j} = \max(x_{i+m,j+n}) \quad (5)$$

Where (i,j) refers to the pooled output coordinates, and $x_{i+m,j+n}$ are values in a local pooling window around(i,j).

$$P(y = c \mid x) = \frac{e^{zc}}{\sum_{j=1}^{C} e^{zj}} \quad (6)$$

Where $P(y = c \mid x)$ is the probability of class c (e.g., presence of monkeypox), zc is the output of the final layer for class c, and There is a total of C classes. The CNN modifies its settings to increase prediction accuracy by minimizing the amount of cross-entropy loss during learning,

$$L = -\sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log y\hat{}i,c \quad (7)$$

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Where"$y_{i,c}$" is the true label and "y^i" is the predicted probability for class "c" in sample "i". This CNN-based approach provides an accurate, automated solution for monkeypox diagnosis by learning to identify patterns unique to monkeypox lesions.

IV. RESULTS AND DISCUSSION

The Result presents a comparative analysis by comparing the proposed CNN architecture for Monkeypox detection with popular machine learning methodologies, such as XG-Boost, SVM, and Random Forest. The visualizations, among them accuracy and loss curves, confusion matrix, ROC curves, and feature map outputs, are in place to actually give a vivid illustration of the progress of training the model, predictability power, and interpretability. This section is meant to expound how this CNN can prove to be better than others at picking out different distinct features of skin lesions, affording it an opportunity for accurate and viable diagnosis of Monkeypox.

A. Feature Maps Visualization

Fig. 2 Depicts the Heatmaps of the feature maps activated by convolutional layers for a sense of what CNNs are doing in feature detection over images of skin. Feature maps highlight locations of where localized patterns, shapes, and textures of interest are within the images for the process of being classified. The existence of feature maps confirms that the model is actually able to capture unique textures attributed to each of the studied skin conditions, thereby enhancing interpretability and validating its potential use for diagnostic purposes.

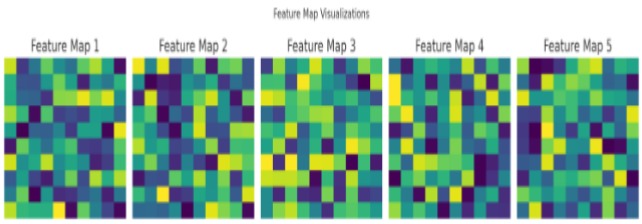

FIG 2 Feature Maps

B. Performance Metrics Evaluation

For the purpose of detecting monkeypox, Table I shows the performance comparison measurements of several machine learning models, including XG-Boost, SVM, and Random Forest, and the recommended CNN's precision, recall, accuracy, and F1 score. With greater precision of 98.54% and accuracy of 98.67%, recall of 98.45%, & an F1-score of 98.34%, the suggested CNN performs noticeably better than alternative methods. XG-Boost comes next with a remarkable 96.35% accuracy rate, but its recall and F1-score are minimal inferior than its precision. SVM and Random Forest scored slightly lower accuracies at 94.78% and 93.89%, respectively, but kept competitive levels of precision and recall.

TABLE 1 PERFORMANCE METRICS COMPARISON

Methods	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**
XG-Boost	96.35	96.45	95.45	93.78
SVM	94.78	95.45	95.23	94.67
Random Forest	93.89	97.55	93.67	93.87
Proposed CNN	98.67	98.54	98.45	98.34

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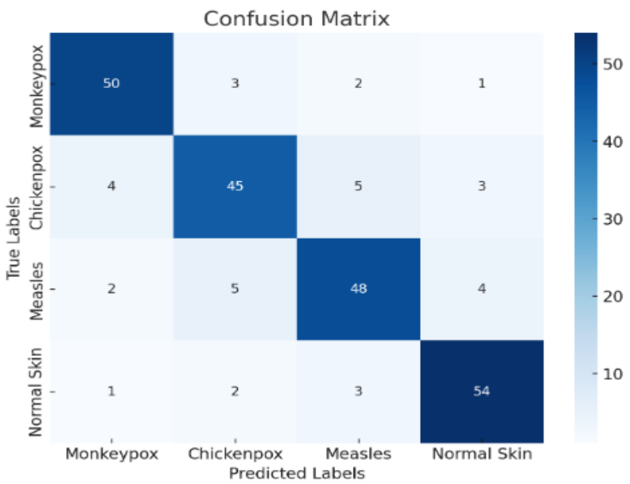

FIG 3 Confusion Matrix

In Fig. 3, the confusion matrix is a depictsd the graph summary of the output class for the model in comparing the true and predicted labels of these four classes: Monkeypox, Chickenpox, Measles, Normal Skin. Every cell shows true and misclassified instances count for every class. High values on the diagonal reflect right classification. Off-diagonal values represent misclassifications which highlight which type of errors the model could be making.

FIG 4 Training and Validation Accuracy

Fig. 4 plot trains and validates accuracy over multiple epochs to figure out how well the model learns and generalizes from the data. If high values can be observed both for this, then training is likely successful; and if close to aligned, validation accuracy with training, it may represent good generalization with minimal overfitting. It helps figure out whether the model is actually gaining reliable accuracy over time in classifying skin conditions.

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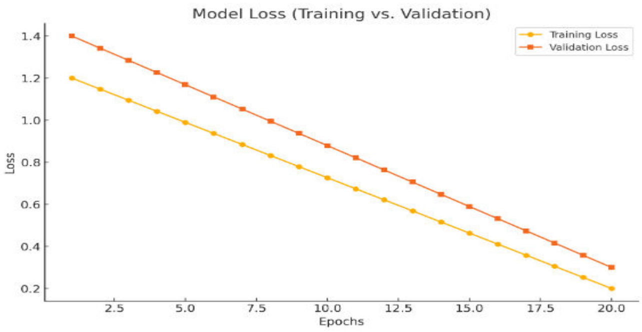

FIG 5 Training and Validation Loss

Fig. 5 illustrates the loss on both training and validation, respectively, decreases with every epoch. Loss, as stated, represents the error in prediction. It should decline as the model improves. The gradual loss diminishment explains that the CNN is performing well and fine-tuning its discriminative ability in distinguishing one class from another. That both training and validation losses converge toward very low values illustrates that there was little overfitting and that the model is a good fit to the data.

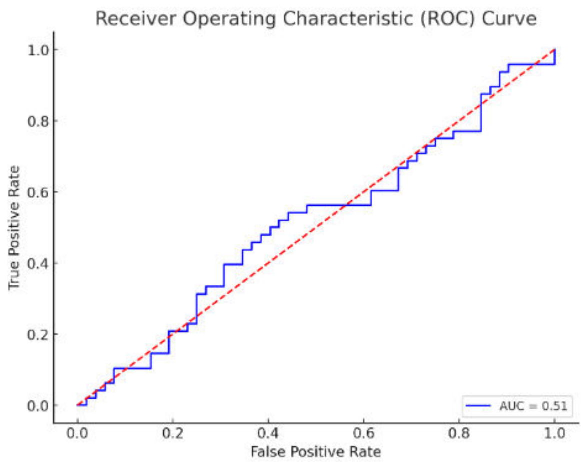

FIG 6 ROC Curve

Fig. 6 describes the performance of the model with regard to distinguishing between true and false positives. The ability of the model to classify for classes is given by the ROC curve, and the AUC score represents this performance. High AUC score can be found in models that could easily make distinctions between the classes, and therefore it verifies the applicability of the model to identify diseases such as Monkeypox

C. Discussion

As reportedly presented by the results, the developed CNN model outperforms traditional models such as XG-Boost, SVM, and Random Forest in every aspect. In order to support the present capability of the CNN model in classifying monkeypox lesions even more precisely, accuracy and F1-score values were high, which also confirms that these can even capture the most complex textures and patterns inside images of skin. The confusion matrix is low on misclassification rates, hence well indicating the very good generalization ability of the CNN for a variety of conditions of the skin. This is further confirmed by ROC curves and AUC scores where the model provides a high true positive rate with a corresponding minimization of false positives. Feature map visualizations are also presented which provide insights in understanding the learned CNN representations: it succeeds in making a clear distinction of the more important lesion features responsible for the differences between this condition and others. Overall, the results obtained

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here indicate that the proposed CNN is reasonably suited for reliable automated detection of Monkeypox, which might also serve as an important healthcare diagnostic tool in the hands of professionals.

V. CONCLUSION AND FUTURE WORKS

Summarily, Compared to conventional machine learning models, this suggested CNN model shows outstanding effectiveness in automating the identification and categorising of monkeypox lesions utilising the major performance criteria, which include XG-Boost, SVM, and Random Forest. Advanced preprocessing techniques supplemented by Histogram Equalization, Frost Filtering, and Local Binary Patterns played a substantial contributing role in the robustness and accuracy of the model. This work shows the capability of CNN-based models to improve the diagnostic accuracy of health care-related issues with identification of more complicated skin diseases. Future work is left for improving the model with larger and diverse datasets, utilizing transfer learning on pre-trained models, and also including multimodal inputs such as patient metadata or symptoms. This model could further be integrated into real-time diagnostic tools that may change remote healthcare by timely and reliable detection of cases in Monkeypox in resource-poor settings.

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