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Deep Learning Framework for Optimizing Early Detection of Measles Using Transfer Learning

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ABSTRACT

Measles is a highly infectious viral disease that can have serious health consequences. Accurate and early diagnosis is crucial. This study aims to enhance automated classification and early detection of this disease. To address the class imbalance, we augmented the dataset of normal images. Spatial features were extracted using convolutional neural networks, and traditional classifiers, including support vector machine, Random Forest, logistic regression, and k-nearest neighbors were applied to these features. Initial classification accuracy based solely on spatial features was as follows: Random Forest 63%, SVM 63%, KNN 60%, and Logistic Regression 63%. Through 10-fold cross-validation, mean accuracies were recorded as 65% for RF, 62% for SVM, 60% for KNN, and 61% for LR. Despite these initial results, the implementation of transfer learning led to significant improvements. By extracting probabilistic features from spatial features using RF and KNN models and concatenating these derived features, classification accuracy was substantially enhanced. The improved model achieved 99% accuracy for RF, SVM, and LR, with KNN reaching 98%. Cross-validation confirmed the robustness of the models, with a mean accuracy of approximately 98% and minimal standard deviations of 0.01. The findings demonstrate that combining transfer learning with traditional classifiers improves the efficiency and accuracy of lesion images. This approach shows significant potential for clinical applications.

INTRODUCTION

The measles virus is exceptionally spreading viral disease caused by the rubeola [1] virus, predominantly affecting children but capable of infecting individuals of all ages. It is characterized by fever, cough, rhinorrhea, conjunctivitis, and a distinctive rash that begins on the face and spreads to the body. Measles is transmitted through airborne respiratory droplets, allowing for efficient spread. The virus can survive on surfaces and in the air for a significant duration, contributing to its contagious nature.

Early identification is crucial for controlling and preventing disease transmission. Given its high contagiousness [2] infected individuals are capable of spreading the virus Within an eight-day period centered on the onset the characteristic rash. Swift identification and isolation of cases play a pivotal role in curtailing further spread, particularly in settings such as schools and healthcare facilities. Furthermore, effective vaccination campaigns are integral in containing outbreaks and protecting unvaccinated individuals, including those with medical contraindications for vaccination. Additionally, timely detection supports the surveillance and monitoring of measles outbreaks, providing critical data for evaluating vaccination program effectiveness and identifying regions with insufficient immunization coverage. This facilitates prompt public health responses, preventing large-scale outbreaks and reducing the global burden of measles.

In 2022, the Democratic Republic of the Congo, along with other countries, [3] Nigeria, and Pakistan, reported significant measles outbreaks, underscoring the ongoing challenges in achieving global measles control. These outbreaks underscore the essential need for sustained efforts to strengthen immunization programs, improve healthcare accessibility, and address factors contributing to vaccine hesitancy. The World Health Organization (WHO) continues to collaborate with nations and partners to enhance measles surveillance, conduct outbreak responses, and execute vaccination campaigns, with the ultimate goal of reducing measles incidence and achieving global eradication.

The measles virus initially infects the respiratory tract and then spreads throughout the body. A 10 to 14-day incubation period precedes the onset of symptoms, which typically start with nonspecific manifestations with symptoms ranging from mild to moderate fever, persistent cough, rhinorrhea, and conjunctivitis. As the disease progresses, a characteristic rash emerges, beginning on the face and upper neck before spreading downwards. This rash, accompanied by a fever exceeding 40 °C (104 °F), manifests approximately 3-5 days following the initial symptoms.

Vulnerable groups like young children, pregnant women, and those with weakened immune systems are at a higher risk of severe measles complications [4]. These complications can include diarrhea, ear infections, and pneumonia, which can have life-threatening consequences. More serious consequences encompass encephalitis (brain inflammation), potentially resulting in permanent neurological damage.

Moreover, early detection of measles skin disease [5] is paramount for several reasons. Timely diagnosis enables prompt medical intervention, which can mitigate symptom severity and reduce the risk of complications. Supportive care, encompassing hydration, nutrition, and treatment of secondary infections, significantly enhances patient outcomes.

LITERATURE REVIEW

A systematic review of the available research on measles was performed shown in Table 1. The study addresses the classification challenges of monkeypox, a viral infection that gained significant attention following the COVID-19 outbreak, and was classified as a global public health emergency by the WHO. Traditional classification methods struggle with the accurate identification of monkeypox due to its similarities with other pox viruses [6] and there are additional concerns regarding the security and privacy of sharing sensitive medical data. To address these issues, the researchers propose an innovative framework integrating DNN federated learning for secure medical data categorization. The FL-based framework proposed comprises three primary elements, the use of a CycleGAN to increase the training data, the employment of Vision Transformer (ViT), ResNet50, and MobileNetV2. This research utilized publicly available datasets, and demonstrated a significant performance of 97.90%.

The distinction between monkeypox and measles is explored through the lens of image classification using deep learning methods [7]. This study demonstrated the effectiveness of this approach by achieving a high accuracy rate of 83.33% after 15 training epochs. This research emphasizes the potential of deep learning in accurately distinguishing between visually similar diseases, thereby improving diagnostic accuracy and public health management.

Detection of skin diseases is crucial for timely intervention and management [8]. Addressing the complexities of diagnosing skin conditions such as blisters, rashes, lesions, papules, and reddened skin, the research leverages transfer learning with pre-trained models originally developed for the Imagenet Dataset. The objective is to utilize these models—ResNet50, DenseNet121, EfficientNetB5, and Xception—for feature extraction and classification of measles, monkeypox, chickenpox, and normal skin. The framework integrates convolutional and pooling layers from these models. The study employs the monkeypox dataset to validate the proposed model. Results demonstrate that Xception outperformed other models, achieving notable training accuracy of 98.39%, validation accuracy of 96.46%, and testing accuracy of 95.80%. Efficacy of transfer learning in enhancing the accuracy and reliability of automated skin disease diagnosis systems, thereby contributing to improved public health outcomes and patient care.

This study has proposed the use of deep learning approach [9] YOLOv5 for detection of diseases images. Compared to traditional manual examination methods, these approaches offer the potential to minimize human error and reduce the time required for diagnosis. For instance, the YOLOv5 model shows promise in accurately differentiating between measles and normal cases across diverse medical images. Evaluation of the model using the MSID dataset demonstrated an impressive 92% accuracy.

This study automates the detection of mpox using computer aided methods [10]. Four pre-trained models AlexNet, ResNet18, ResNet50, and a hybrid ResNet18 and GoogleNet are employed with transfer learning. This technique is better than any individual CNN model in identifying Monkeypox accurately by achieving 91.57% accuracy, and this demonstrates the possibility of utilizing deep learning to enhance early disease identification and healthcare delivery systems.

This research paper is about examining how deep learning methods can be effective in automatically recognizing [11] monkeypox skin lesions using datasets obtained from Kaggle. Deep learning models like ResNet50, InceptionV3, VGG-16,and GoogLeNet. From these models, GoogLeNet achieved the highest accuracy with 88.27% which was better off compared to VGG-16 (83.85%), ResNet50 (85.38%) and InceptionV3 (86.37%). This finding indicates that deep learning techniques have a potential for enhancing the diagnosis of monkeypox, especially through use of specific methods such as GoogLeNet thereby underscoring the significance of having complete training sets as a way forward towards this essential domain of disease detection.

This research presents three DL models InceptionV3, MobileNetv3, and Densenet201 [12] using transfer learning on Monkeypox Skin Image Dataset 2022 that consists of four different classes. Their results suggest that, for recognition of monkeypox lesions from skin images that have been digitized, the InceptionV3 model was able to achieve a significant accuracy (93.59%) and would increase diagnostic values by transfer learning algorithms now in place. In the future, further implementation of increased and diverse well-designed training datasets used in these models may bring a step forward to the use of more accurate deep-learning modes for the detection of monkeypox.

The study [13] evaluated the efficacy of various machine learning classifiers in predicting measles cases in Ghana. A comparative analysis was conducted between six classifiers, including random forest (RF), and traditional methods using a cross-sectional dataset of suspected measles cases. RF consistently outperformed other models, demonstrating superior sensitivity (0.88), specificity (0.96), ROC (0.92), and overall accuracy (0.92). These findings underscore the potential of RF as a promising tool for early-stage measles prediction.

This literature review focuses on the global [14] emergence of Monkeypox (mpox) as a significant public health threat, exacerbated by its spread to over 100 nonendemic countries amid the ongoing COVID-19 pandemic. Mpox shares clinical similarities with chickenpox and measles, posing challenges in accurate and timely diagnosis. The study aims to expedite and enhance mpox diagnosis through deep learning (DL) models, leveraging their capabilities in image-based diagnostics to mitigate potential misdiagnosis. The research emphasizes the adoption of DL for automated early detection, evaluating performance using publicly available datasets. Comparative analysis of VGG19, CNN, Inception v3, ResNet 50. Inception v3 as achieving the highest classification accuracy (96.56%) for mpox skin lesions, underscoring its potential for effective diagnostic applications in public health emergencies.

This study explores the application of Deep Learning for detecting mpox in skin lesion images captured via smartphone cameras, addressing the challenge of limited mpox datasets through Transfer Learning techniques [15]. Initially, a curated dataset was created by manually selecting and preprocessing publicly available image data. Multiple convolutional neural networks were evaluated with k-fold, with an additional analysis conducted to assess model performance across different skins. Best performing models through quantization for mobile deployment, evaluating metrics such as classification accuracy, memory efficiency, and processing times. MobileNetV3 shows top performance, achieving an F-1 score of 0.928 for binary classification and 0.879 for multi-class tasks.

This study introduces AI hybrid system designed to detect mpox [16], addressing its transmission dynamics from animals to humans and from one person to other spread through respiratory droplets. Employing an open-source image dataset encompassing chickenpox, measles, monkeypox, and normal skin classes, the study initially addresses class imbalance through extensive data augmentation and preprocessing techniques. Deep learning models including MobileNetV3, SE-ResNet, RepVGG, InceptionV4, MnasNet, Xception, and CSPDarkNet are utilized for monkeypox detection. The hybrid AI system achieves notable performance metrics with an 87% accuracy and contributing to advancements in AI-driven disease diagnosis in diverse clinical contexts.

Table 1

Literature summary analysis of measles in medical image detection for predicting skin diseases

#	Year of Publication	Dataset	Technique	Accuracy
1	2023	Dataset of skin lesions and MISD Dataset	CycleGAN, MobileNetV2, Vision Transformer (ViT), ResNet50, Federated Learning	97.90%
2	2023	Monkeypox Skin Images Dataset from Kaggle	Transfer Learning, VGG-16	83.33%
3	2023	Monkeypox Skin Images Dataset (MSID)	ResNet50, DenseNet121, EfficientNetB5, Xception	96.46%
4	2023	MSID	YOLOv5	92%
5	2023	Monkeypox Images from Different Websites	ResNet50, AlexNet, ResNet18, Hybrid ResNet18 and GoogleNet	91.57%
6	2022	Lesion Image dataset	VGG-16, ResNet50, InceptionV3, GoogLeNet	88.27%
7	2023	Monkeypox Skin Image Dataset 2022	InceptionV3, MobileNetV3, DenseNet201	93.59%
8	2023	Suspected measles cases in Ghana	Random Forest (RF), traditional methods	92%
9	2022	Mpox Skin Lesion Images Dataset	CNN, VGG19, ResNet 50, Inception v3, Autoencoder	96.56%
10	2023	Curated dataset	Transfer Learning, MobileNetV3Large, Quantization	87.9%
11	2023	Open-source Image Dataset	InceptionV4, CSPDarkNet, MobileNetV3, MnasNet, SE-ResNet, RepVGG, LSTM, Xception	87%

Research Gaps

According to prior research, notable deficiencies exist in the current understanding of the following areas:

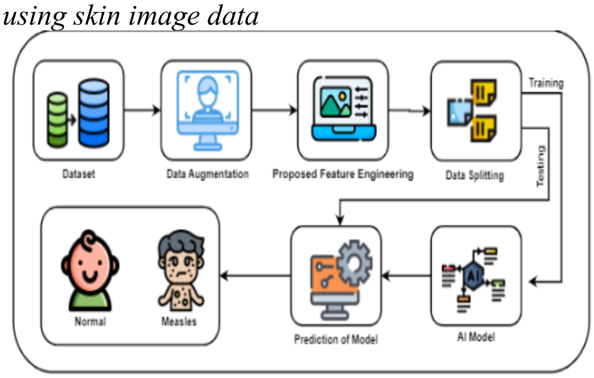
- The majority of existing works in this area suffer from imbalanced datasets.
- Achieve optimal efficiency in detecting lesion diseases with exceptional efficiency.

MATERIALS AND METHODS

Proposed Methodology

Our proposed methodology resolves to employ a sophisticated model for forecasting measles skin disease, as depicted in Figure 1. The utilization of this advanced model aims to enhance the accuracy and performance of predicting measles skin disease. The research utilizes a dataset of lesion images to apply advanced machine and deep learning techniques, specifically the CNN-RK technique, which leverages transfer learning for feature engineering. This approach aims to extract impactful features from the image data to accurately predict measles disease with high performance. We divided the features dataset into two subsets at an 80:20 ratio. The larger subset, spanning 80% of the data, is dedicated to training, while 20% is used validation. The fine-tuned approach demonstrates superior performance in accurately detecting skin disease based on lesion images.

Figure 1
An analysis of the methodological architecture in our approach for diagnosing measles disease using skin image data



Lesion Images Dataset

Our study experiments utilized the lesion disease images dataset from the well-known repository Kaggle [17]. This dataset comprises 1445 files categorized into two classes one is measles and normal, as presented in Figure 2. The dataset breakdown shows that there are 564 images in the measles class and 881 image in the normal class, indicating an imbalance in the label distribution. Furthermore, Figure 3 illustrates the image data and their corresponding target labels.

Figure 2
Lesion images data distribution analysis

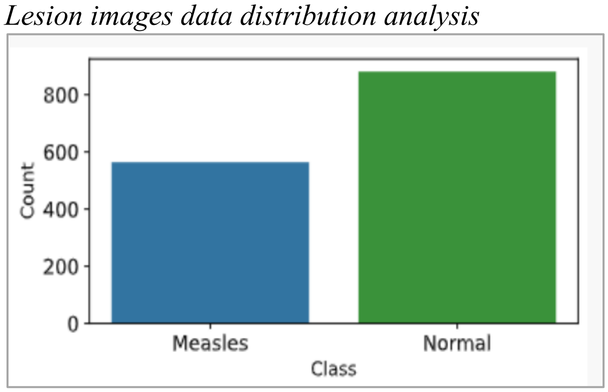
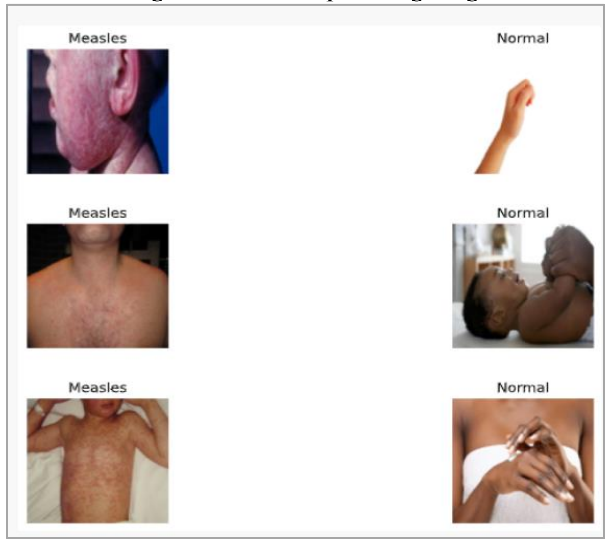


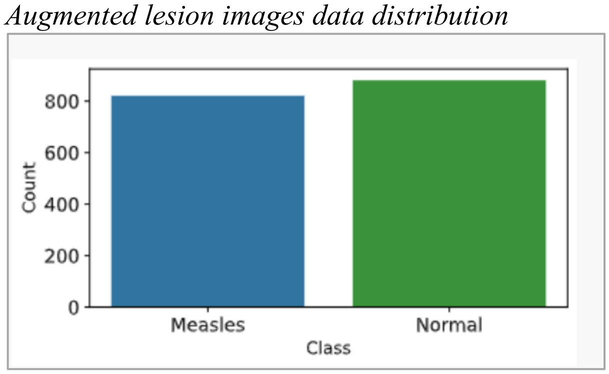
Figure 3
Measles images with corresponding target labels



Data Augmentation

After augmentation, the measles class has been enriched with 821 images, significantly improving the dataset balance crucial for robust model training and evaluation in our research. This augmented dataset addresses the initial imbalance, enhancing the representation of the measles class and facilitating more equitable learning by the model. By mitigating bias and increasing the diversity of the training data. Ultimately, this augmentation not only strengthens the dataset's suitability for training but also enhances algorithmic performance, ensuring more accurate and reliable outcomes. The augmented dataset is shown in Figure 4.

Figure 4
Augmented lesion images data distribution



Feature Engineering using Transfer Learning

A new feature engineering technique based on transfer learning [18] is proposed for detecting measles using human body image data. Figure 5 demonstrates the operation of this technique. The

CNN-RK method integrates three approaches to transfer learning, creating an innovative feature set. Initially, spatial features are extracted from lesion skin images dataset using CNN. These features are then analyzed using RF and KNN, generating a probabilistic set of features [19] derived from the spatial data shows in Figure 6. Probabilistic features are subsequently used to develop detection methods for measles from images of different body parts.

The proposed technique has significantly improved the accuracy of measles detection from images. The study's methodology is designed around high-performance prediction models for skin diseases, as shown in Figure 1. The CNN-RK method for feature engineering is used to extract features, resulting in high-accuracy predictions for measles. An 80:20 ratio is utilized to divide the features into training and validation sets [20], with 80% of the data being used for training and 20% for evaluation. The optimized method provides high-performance accuracy for detecting measles from images of various body parts. [21].

Extraction of Spatial Features

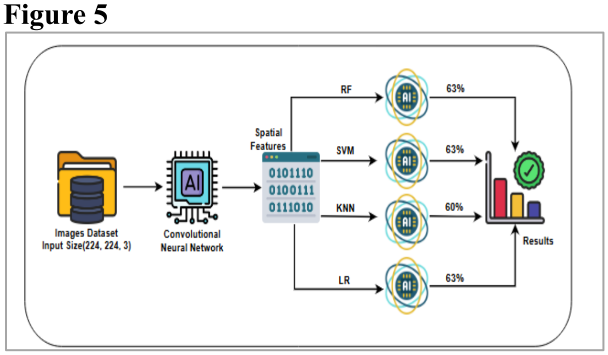
Consider our dataset A contains B images, every image represented by a matrix [22] $\mathbf{C} \in H^{I \times J}$, where I represents height and J represents width. Our aim is to use a 2D CNN model to obtain spatial features [23]. CNN captures image patterns by applying convolutional filters to detect local features such as edges, textures, and shapes at various layers of abstraction. m-th layer of the CNN, the output feature map is denoted as $\mathbf{X}m$. At layer m, the convolution operation [24] is expressed as:

$$\mathbf{X}m = \sigma(\mathbf{W}m * \mathbf{X}m\text{-}1 + \mathbf{b}m) \quad (1)$$

In this expression:

- $*$ represents the convolution operation.
- $\mathbf{W}m$ is the convolutional filter.
- $\mathbf{b}m$ represents the bias.
- $\sigma(\cdot)$ represents the activation function.

Figure 5



Applying different ML models on spatial features to predict measles disease Firstly, a CNN model is applied to an image dataset to extract spatial features, where the image size is 224 × 256, the batch size is 100, and the input channels are 3 with a softmax activation function. After extracting the spatial features, traditional models KNN, SVM, RF and logistic regression are applied to these features. The results were not as expected: RF, SVM, and LR yielded 63% accuracy, while the KNN model showed results at 60%. However, there is still significant room for improvement.

Probabilistic Features

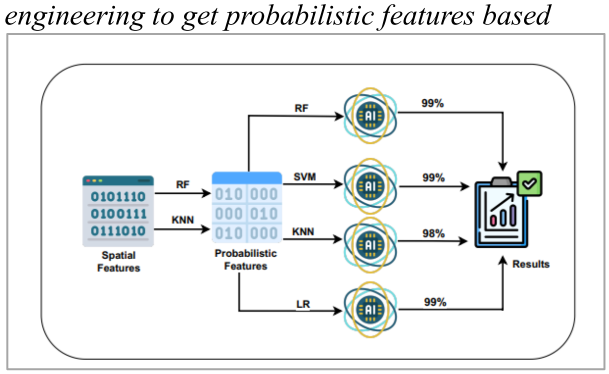
Assume we have input data denoted by M and an output variable denoted by N. A model can be created to predict N based on M by examining the co-occurrence of M and N relative to the frequency of M alone.

Process of extracting features converts the raw data M into useful features represented by F. Here, F encapsulates the extracted relevant information from the input data.

$$F = f(M) \quad (2)$$

Figure 6

Proposed workflow architecture for feature engineering to get probabilistic features based



Algorithm of Proposed Workflow:

Algorithm 1 CNN-RK Algorithm

Input: Measles and normal images of human skin.

Start;

1. $F_{cnn} \leftarrow$ CNNprediction (IMG)
   F_{cnn} is the set of spatial features that is extracted from image dataset (IMG).
2. $F_{rf} \leftarrow$ RFprobabilities prediction (F_{cnn})
   Frf is the set of probabilistic features that are extracted from Fcnn.
3. $F_{knn} \leftarrow$ KNNprobabilities prediction (F_{cnn})

Fknn is the set of probabilistic features that are extracted from Fcnn.

4. $F_{Prob} \leftarrow F_{rf} + F_{knn}$
5. *FProb is the final required probabilistic features.*

End;

Output: Probabilistic Features

Dataset Splitting

Splitting a dataset is an essential process. Its main goal is to divide the dataset between two parts: a training part and another for validation purposes. We used an 80% : 20% dataset split in our study, which meant that the majority were used to train the model, and the remainder of the images were saved for testing. The test set enables us to evaluate performance of model on untested dataset, while training set aids in fine-tuning the model's parameters. This splitting method works well to prevent overfitting, a frequent problem. that happens when we developed model with small dataset. Essentially, data splitting plays a vital role in constructing resilient and dependable ML models.

Applied Deep Learning and Machine Learning Models

Deep learning and machine learning models shows outstanding success in accurately classifying images [25]. One of the most widely adopted deep learning techniques, CNN, has gained recognition for its outstanding results in detection. CNN extracts spatial features from image and creates complicated data representations by applying numerous layers of filters. Better performance is achieved by training machine learning models for picture categorization using these spatial features [26].

In our research, we employed CNN for image classification and spatial feature extraction. These spatial features were then combined with machine learning algorithms like RF, SVM, LR, and KNN [27]. Additionally, probabilistic features were derived from the spatial features. The use of ML techniques led to exceptional performance in predicting measles. Detailed analysis and presentation [28] of the layer architecture of CNN model [29] is shown in Table 2.

Table 1

Structural layers of the CNN model

CNN Layers	Shapes	Parameters
Conv-2D Layer	(None,222,222,64)	1,792
Maxpooling-2D Layer	(None, 111, 111, 64)	0
Conv2D- Layer	(None, 109, 109, 32)	18464
MaxPooling-2D Layer	(None, 54, 54, 32)	0
Conv2D Layer	(None, 52, 52, 128)	36,992
MaxPooling-2D Layer	(None, 16, 16, 128)	0
Flatten Layer	(None, 86528)	0
Dense Layer	(None, 600)	51,917,400
Total Parameter		51,974,830

Hyperparameter Tuning

Finding the best hyperparameters for a specific model is called hyperparameter tuning, and it is a fundamental procedure in machine learning. This procedure comprises assessing the model's performance on a different test set and testing a range of hyperparameter variables. Finding the hyperparameter combination that yields batter results on validation. Hyperparameter tuning can greatly increase the effectiveness of machine learning algorithms, it is crucial. For your reference, Table 3 contains the specifics of the hyperparameter optimization for our applied approaches.

Table 2

Hyperparameter Tuning for Classification Techniques

Technique	Hyperparameters Tunning
CNN	activation='softmax', optimizer='adam', loss='categorical_crossentropy'
RF	n_estimators=300, max_depth=10, random_state=10,
SVM	kernel='rbf', C=0.4, gamma=scale, random_state=100
KNN	n_neighbors=10, weights=uniform, random_state=25
Logistic Regression	Max_iter=1000, random_state=10

RESULTS

This section focuses into the analysis of the applicable AI based approaches, validation, and performance. Using measles imaging data, we present a relative description of investigational setting and outcomes. Performance indicators like recall, precision, accuracy, and f1-score are used to assess the model's efficacy. This section is essential to fully evaluating how well the suggested deep learning and machine learning techniques can be applied to real-world issues.

Spatial Features

These features were obtained from image data utilizing a deep learning-based CNN. Subsequently, RF [30], SVM, KNN, and Logistic Regression models were employed to train and evaluate the spatial features. The performance metrics, including accuracy, precision, recall, F1-score, and Support, are presented in Table 4.

Table 3

Performance Metrics for Classification Techniques on Spatial Features

Techniques	Accuracy in Percentage	Target	Precision	Recall	F1-score	Support
RF	0.63	Measles	0.50	0.31	0.38	106
		Normal	0.67	0.82	0.74	183
		Average	**0.61**	**0.63**	**0.61**	**289**
SVM	0.63	Measles	0.99	0.02	0.04	110
		Normal	0.62	0.99	0.77	179
		Average	**0.77**	**0.63**	**0.49**	**289**
KNN	0.60	Measles	0.47	0.40	0.43	110
		Normal	0.66	0.40	0.69	179
		Average	**0.59**	**0.60**	**0.59**	**289**
Logistic Regression	0.63	Measles	0.80	0.04	0.07	111
		Normal	0.62	0.99	0.77	178
		Average	**0.69**	**0.63**	**0.50**	**289**

The comparative performance metrics for classification techniques on spatial features for measles classification reveals varying performance across different models shown in Table 4. RF and SVM achieved an accuracy of 63%, with SVM showing high precision for the normal class but lower scores for measles detection. K-Nearest Neighbors (KNN) demonstrated a slightly lower accuracy at 60% but showed better precision in classifying both measles and normal cases than SVM and RF. Logistic Regression exhibited comparable results with an accuracy of 63% and precision scores similar to SVM and RF. Overall, while KNN and Logistic Regression show promise, significant improvements are necessary to enhance the accuracy and precision of measles detection with spatial features.

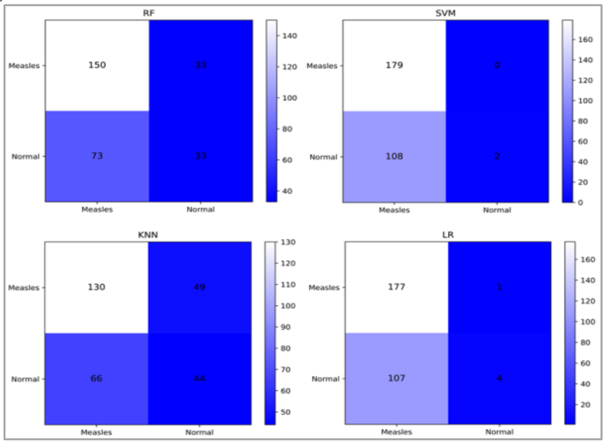
Bar chart in Figure 7 depicts a comparative analysis of the performance of various ML models using spatial features. Upon visual inspection, it is evident that machine learning models displayed unsatisfactory performance when dealing with spatial features. Specifically, RF, SVM, and Logistic Regression techniques achieved an accuracy score of 63%, while KNN achieved the lowest accuracy at 60%, significantly the need for improvement. In conclusion, there is a need to enhance performance to effectively detect measles in normal-based image datasets.

Figure 7

The performance metrics assessment of ML models with spatial features using bar charts.

In the analysis depicted in Figure 8, a study focusing on the application of machine learning methodologies incorporating spatial features is illustrated through a confusion matrix. The depiction of model predictions against the true labels within a given dataset is encapsulated in a confusion matrix, enabling the identification of areas necessitating improvement and facilitating an in-depth understanding of the model's strengths and weaknesses. The outcome of this investigation suggests that the integration of spatial data in machine learning models yielded suboptimal performance, particularly in the context of image classification, which was associated with elevated error rates.

Figure 8
Confusion matrix of ML models on spatial features.



Probabilistic Features

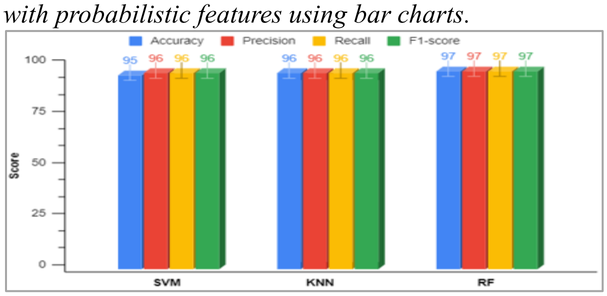
After applying machine learning methodologies to extract spatial features and subsequently derive probabilistic features, a comprehensive performance evaluation is conducted. The probabilistic attributes are acquired through the utilization of machine learning models for spatial feature extraction. The efficacy of ML-based methodologies is then ascertained through their training and evaluation using these probabilistic features. The study shows the effectiveness of various machine learning techniques leveraging probabilistic features, as detailed in Table 5, revealing that the utilization of probabilistic features consistently yields superior results across all machine learning techniques.

Table 5
Performance metrics for classification techniques on probabilistic features

Techniques	Accuracy in Percentage	Targeted Classes	Precision	Recall	F1-score	Support
RF	0.99	Measles	0.98	0.99	0.99	111
		Normal	0.99	0.99	0.99	178
		Average	**0.99**	**0.99**	**0.99**	**289**
SVM	0.99	Measles	1.00	0.97	0.98	118
		Normal	0.98	1.00	0.99	171
		Average	**0.99**	**0.99**	**0.99**	**289**
KNN	0.98	Measles	0.99	0.96	0.97	118
		Normal	0.97	0.99	0.98	171
		Average	**0.98**	**0.98**	**0.98**	**289**
Logistic Regression	0.99	Measles	1.00	0.96	0.98	111
		Normal	0.98	1.00	0.99	289
		Average	**0.99**	**0.99**	**0.99**	**289**

The LR, SVM, and RF models achieved an accuracy of 99%, while the KNN model demonstrated considerable promise with a score of 0.98. Furthermore, high performance measures were observed for each class. Based on this investigation, it can be inferred that the utilization of retrieved probabilistic characteristics for identifying measles in photos results in the attainment of the highest performance scores.

Figure 9
The performance metrics assessment of ML models with probabilistic features using bar charts.

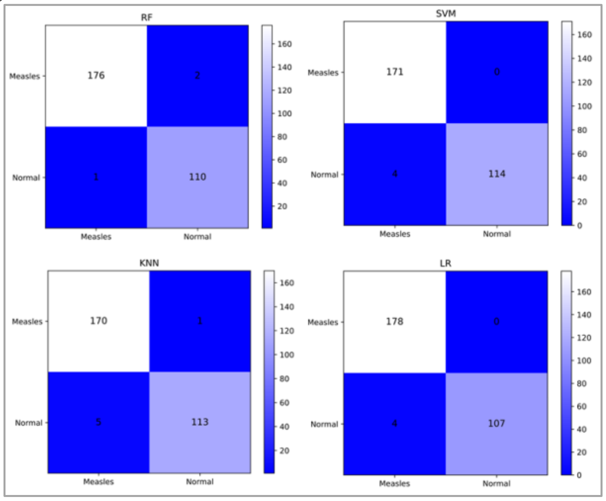


Performance of bar chart in Figure 9 compares the effectiveness of machine learning models that use probabilistic features. The study's findings show that accuracy scores are much increased when probabilistic characteristics generated from spatial variables are included. The CNN-RK method that has been suggested gets the highest accuracy score in this study. In summary, all machine learning techniques tested outperform each other in terms of measles detection.

The confusion matrix for probabilistic a feature-based machine learning techniques is represented graphically in Figure 10. Notable scores from the machine learning models' performance evaluation illustrate how well employing probabilistic features works. Extensive study validates that a low mistake rate has been achieved through the use of probabilistic features.

Figure 10

Evaluation of machine learning techniques through confusion matrix analysis of probabilistic features



K-Fold Cross Validation

The outcomes of the model generalization were evaluated using k-fold cross-validation, as displayed in Table 6. Each model underwent assessment using 10 folds to evaluate the feature sets. The results indicate that incorporating retrieved spatial characteristics into the cross-validation process resulted in inferior performance scores and elevated standard deviation values. Conversely, the analysis highlights superior accuracy scores and a minimal standard deviation of 0.01 when employing probabilistic features. Notably, our proposed CNN-RK approach using probability features achieves the highest k-fold accuracy of 0.98. In conclusion, the results demonstrate that all techniques are validated and capable of effectively detecting measles image data in a generalized manner.

Table 6

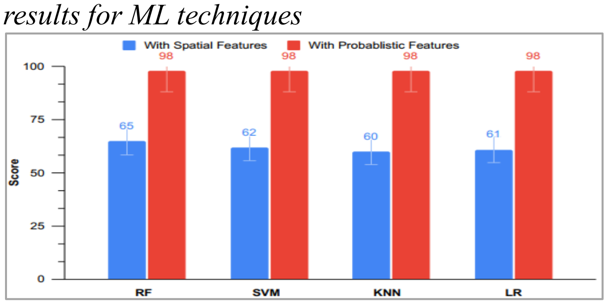
The K-Fold accuracy and standard deviation for classification techniques

Techniques	Spatial Features		Probabilistic Features	
	K-Fold Results (%)	Standard Deviation (+/-)	K-Fold Results (%)	Standard Deviation (+/-)
RF	0.65	0.04	0.98	0.01
SVM	0.62	0.01	0.98	0.01
KNN	0.60	0.03	0.98	0.01
Logistic Regression	0.61	0.04	0.98	0.01

The bar chart representation of the model performance assessment based on 10-fold cross-validation using both feature sets is depicted in Figure 11. The analysis indicates that superior performance scores are attained by leveraging probabilistic features. Proposed method obtained a k-fold validation accuracy of 98% with a minimal standard deviation of 0.01%. The findings suggest that spatial features yield poor performance in contrast to the enhanced performance achieved with probabilistic features.

Figure 11

Bar chart representation of k-fold validation results for ML techniques



However, using probabilistic features, we get score of 98%, demonstrating the model's generalization capability for detecting measles.

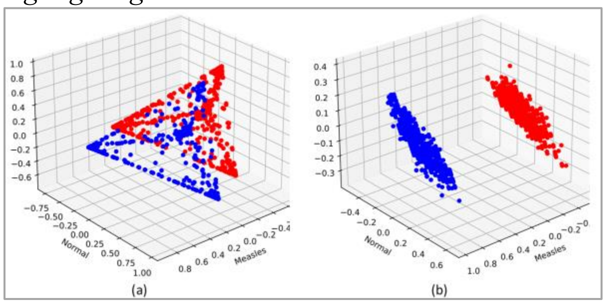
Comparative Analysis of Spatial and Probabilistic Features

Spatial features derived from the measles images dataset using CNN demonstrates a significant degree of non-linear separability. The suboptimal performance of the ML models can be attributed to the non-linear nature of this spatial features. To address this issue, we propose the CNN-RK method, which leverages KNN and RF models to generate a probability-based feature set. This approach results in a feature collection with enhanced linear separability, thereby substantially improving the discrimination between target classes.

The experimental findings from our study illustrate that the CNN-RK approach significantly increase the performance of ML techniques Visualizations in Figure 12(a) depicts the space analysis for features, confirming enhanced performance. Moreover, Figure 12(b) illustrates that the spatial features lack linear separability.

Figure 12

Spatial and probabilistic feature space analysis highlighting class distribution



Comparisons with Other State-Of-The-Art Studies

We have compared the performance of our proposed study with previous studies shown in Table 7. They used deep and machine learning methods, achieving a maximum performance score of 95.42%. In contrast, our research utilized transfer learning approach for feature engineering, which led to a significant improvement in performance. Our analysis shows CNN-RK with transfer learning-based features achieved the highest accuracy of 99% in classification of measles.

Table 7

Proposed model comparison analysis of measles in medical image detection for predicting skin diseases

#	Year of Publication	Dataset	Technique	Accuracy
1	2023	Dataset of skin lesions and MISD Dataset	CycleGAN, MobileNetV2, Vision Transformer (ViT), ResNet50, Federated Learning	97.90%
2	2023	Monkeypox Skin Images Dataset from Kaggle	Transfer Learning, VGG-16	83.33%
3	2023	Monkeypox Skin Images Dataset (MSID)	ResNet50, DenseNet121, EfficientNetB5, Xception	96.46%
4	2023	MSID	YOLOv5	92%
5	2023	Monkeypox Images from Different Websites	ResNet50, AlexNet, ResNet18, Hybrid ResNet18 and GoogleNet	91.57%
6	2022	Lesion Image dataset	VGG-16, ResNet50, InceptionV3, GoogLeNet	88.27%
7	2023	Monkeypox Skin Image Dataset 2022	InceptionV3, MobileNetV3, DenseNet201	93.59%
8	2023	Suspected measles cases in Ghana	Random Forest (RF), traditional methods	92%
9	2022	Mpox Skin Lesion Images Dataset	CNN, VGG19, ResNet 50, Inception v3, Autoencoder	96.56%
10	2023	Curated dataset	Transfer Learning, MobileNetV3Large, Quantization	87.9%
11	2023	Open-source Image Dataset	InceptionV4, CSPDarkNet, MobileNetV3, MnasNet, SE-ResNet, RepVGG, LSTM, Xception	87%
12	Our Study	Lesion Images Dataset	CNN-RK, Optimize Feature Engineering Technique using Transfer Learning	99%

DISCUSSION

The study introduces a feature engineering using transfer learning technique called CNN-RK, which aims to diagnose measles with high accuracy by analyzing human body images. The comparative analysis of classical CNN and various machine-learning models demonstrates batter performance of the proposed CNN-RK model. The extraction of spatial features using 2D-CNN images and different machine-learning models reveal significant improvements in the diagnostic accuracy of measles.

Moreover, the study leverages random forest and k nearest neighbor technique generate probabilistic feature set, which is then used in developing ML models. The CNN-RK model achieves exceptional performance scores, with 98% accuracy for KNN and 99% accuracy for RF, KNN, and LR, along with impressive recall, f1, and precision metrics.

Our study contributes to the advancement of diagnostic techniques for measles, underscoring the potential of advanced transfer learning feature extraction methods in the analysis of human body images. Future research directions could explore the application of similar transfer learning approaches to other medical imaging tasks, further advancing the field of medical diagnostics.

CONCLUSIONS

In conclusion, the research indicates the efficacy of advanced transfer learning feature extraction techniques in diagnosing measles through the analysis of human body images. The results underscore the potential of the proposed CNN-RK model in achieving high accuracy and performance compared to traditional CNN and other machine-learning models. These findings represent a major breakthrough in medical imaging and diagnostics by establishing the path for the development of better and more useful diagnostic tools for measles and possibly other skin diseases.

Abbreviations

The following abbreviations are used in this manuscript:

RF Random Forest
KNN K-Nearest Neighbor
LR Logistic Regression
CNN Convolutional Neural Network
CNN-RK Convolutional Neural Network-Random Forest, K- Nearest Neighbor
MSLD Monkeypox Skin Lesion Dataset

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