Accessible Real-Time Chickenpox Screening for Outbreak Management in Low-Resource Communities

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ABSTRACT

Chickenpox remains a highly contagious disease that is challenging to diagnose swiftly due to the subjectivity of visual assessments and delays in laboratory testing. Exacerbated by declining vaccination rates following the COVID-19 pandemic, the risk of rapid outbreaks in community settings, such as schools and childcare centres, has significantly increased. In low-resource and remote communities where traditional diagnostic expertise is limited, these delays hinder effective disease management. To address this healthcare accessibility gap, this study proposes an affordable, standalone, and real-time chickenpox screening system powered by a Raspberry Pi. The prototype uses deep learning-based image classification to assist with early detection, complemented by a secure, privacy-preserving web interface that enables authorised medical personnel to efficiently monitor cases and validate predictions. To optimize the system for community use, an empirical comparative study between ResNet-50 and MobileNetV2 architectures was conducted using a balanced dataset of 1,000 dermatological images. While MobileNetV2 offered higher sensitivity (recall), the ResNet-50 model demonstrated superior reliability and balanced performance—achieving a validation accuracy of 83.5%, a precision of 87.6%, and an F1-score of 82.5%. Real-time testing confirmed that ResNet-50 minimizes false positives, making it the optimal choice to prevent unnecessary anxiety or intervention during community screening. Ultimately, this work delivers a practical, edge-optimized digital health tool that democratizes disease screening, providing a scalable solution to enhance community health security and mitigate infectious disease outbreaks in underserved regions.

Keywords: Chickenpox screening, Community health, Healthcare accessibility, Outbreak management, Real-time diagnosis

INTRODUCTION

Varicella-zoster virus, commonly known as chickenpox, is a highly infectious ailment [1]. It spreads primarily through respiratory droplets and direct contact with skin lesions or oral secretions [2]. It poses a severe risk to vulnerable populations, particularly infants, pregnant women, and individuals with weakened immune systems [3]. With declining vaccination rates globally, the risk of rapid outbreaks in community settings such as schools and childcare centres has intensified. Early and accurate detection is essential for effective disease containment and outbreak management. However, traditional diagnosis relies heavily on specialized clinical expertise, which is frequently unavailable in remote, underserved, or low-resource areas, leading to critical delays in isolation and treatment [4].

While recent technological advancements in deep ensemble learning—utilizing models such as VGG-16, VGG-19, and ResNet-50—have demonstrated high classification accuracies (up to 93%) in distinguishing chickenpox from similar skin conditions [5], deploying these sophisticated models in everyday community settings remains a challenge. There is a pressing need to translate these artificial intelligence breakthroughs into accessible, practical tools that can be utilized at the edge, outside of traditional, well-funded clinical environments.

To address this gap in healthcare accessibility, this work introduces a low-cost, real-time image classification system powered by a Raspberry Pi. By leveraging a fine-tuned ResNet-50 deep learning model to automatically identify key dermatological features—such as red spots, pustules, and rashes—the system provides a reliable, computer-assisted screening method that supports clinical diagnosis. Designed specifically for low-resource settings, this standalone prototype is both portable and affordable, overcoming the traditional barriers to medical diagnostic tools. Furthermore, the system is paired with a secure, web-based interface for real-time data logging, which locally retains critical information (date, time, images, and diagnostic results) to ensure data integrity. This feature is vital for outbreak management, allowing healthcare providers to efficiently track cases and monitor disease spread while maintaining patient privacy.

The contributions of this study to public health innovation are as follows: (i) the development of an edge-optimized, highly accessible pipeline for real-time chickenpox screening; (ii) an empirical evaluation of MobileNetV2 versus ResNet-50 to determine the most reliable architecture for community-level deployment ; and (iii) the provision of an open-source implementation package and prototype that democratizes dermatological screening in low-resource environments.

RELATED STUDIES

A Convolutional Neural Network (CNN) is a form of Artificial Neural Network (ANN). It has a feed-forward network in structure and possesses a remarkable ability to generalize as compared to other networks with fully connected (FC) layers. Besides, it can come up with highly abstracted representations of objects, especially spatial data, and identify them in a better way [6]. The primary advantage of CNN over its predecessors is that it automatically identifies the relevant features without any human supervision [7]. CNNs have been extensively applied in a variety of different fields, including computer vision [8], speech processing [9], and face recognition [10], among others.

A widely used CNN, similar to a multi-layer perceptron, consists of convolution layers for feature extraction, pooling layers for reducing image size, and fully connected layers for classification [11]. Convolution layers use learned weights to generate feature maps, followed by non-linear activations such as ReLU for modelling complex patterns [12][13]. The author in [14] states that the features set that has been extracted are subsequently forwarded to the pooling layer, and this layer reduces the size of large images while maintaining the most significant information contained within them. The last stage consists of fully connected layers that process the high-level, filtered images and convert them into labelled categories.

CNN Backbone of Object Detection

Convolutional Neural Networks (CNNs) are the backbone for object detection and have made significant advancements in the way objects are detected in computer vision. Not only does object detection tell if an object is present in an image, but it also provides the location of the object in the image. The primary goal of the backbone network, which implements this idea, is to extract features from the photos before they are processed for other related procedures, including the computational localization phase in the object detection process [15].

Meanwhile, the study in [16] explored the selection of CNN backbones for object detection, emphasizing two main factors, which are accuracy and efficiency. They also noted that the choice of the appropriate backbone is crucial, as it dictates the overall performance that follows the Residual Neural Networks (ResNet-50), MobileNet, InceptionV3, Visual Geometry Group-16 (VGG-16) model, etc. Overall, in more precise tasks, more profound and complicated models such as ResNet, are utilized. Conversely, when the critical aspect is latency, light models such as MobileNet are chosen. Therefore, the choice of the backbone depends on the specific needs of the application, as detection precision is usually achieved at the expense of computational complexity.

Deep Learning Approach for Skin Disease

Deep learning serves as the foundation for modern image-based diagnostic systems, with VGG-16 commonly adopted for its simplicity and hierarchical feature extraction [17]. As reported in [18], VGG-16 achieved 81.48% accuracy in classifying skin lesions of monkeypox, chickenpox, and measles, though it is prone to overfitting when datasets are small. Even so, its stable architecture remains a reliable choice for medical image analysis. Keras ResNet, or Residual Neural Network, introduced by He Kaiming's team at Microsoft Research [19], improves CNNs through skip connections to address vanishing gradients and enable deeper training. In [18], ResNet-18 achieved 84.59% accuracy and an F1-score of 84.63% in skin lesion classification, performing well when diseases have similar visual features and high precision and recall are required.

In [20], MobileNetV3 is built to be highly efficient, which makes it ideal for mobile and real-time applications. In the study done by [20] MobileNetV3 was established to possess the ability of 95.73% accuracy and 98.34% specificity of skin disease detection. Depth-wise separable convolution, as well as the Squeeze-and-Excitation blocks, are the basis of a light architecture that offers high accuracy with a low computational load. This qualifies it well in low-resource settings, particularly those with relatively inexpensive imaging devices, including webcams.

The study in [21] trained models such as VGG-16, ResNet50, and SqueezeNet for the accurate detection of Monkeypox, and it proves that AI solutions can be very efficient in the medical field. Under the study, the researchers indicated that VGG-16 provided the best accuracy with 95.6 % accuracy and a high F1-score of 0.92, which makes it a possibility to apply to similar kinds of diseases. Meanwhile, in [22], a lightweight diagnostic system that classifies skin cancer using a combination of machine learning and deep learning utilizing Raspberry Pi 4 has been proposed to achieve accuracy and efficiency. The system achieves an accuracy of 89.8% with low power and CPU usage. The system integrates the XGBoost classifier, Principal Component Analysis (PCA) and VGG-16 for decision-making, to eliminate redundant data, and for feature extraction, respectively. Also, the model applies pre-processing steps like resizing and grayscale conversion to ensure consistent data input. As reported in [23], the convolutional neural networks, which are Xception, MobileNet, and ResNet50, show strong performance in terms of both fast execution time and accuracy in identifying skin lesions from affected images. Besides, it was observed that the Xception and MobileNet were able to work with an accuracy of 98.6% and 97.6%, respectively. Hence, these models were efficient for web and mobile applications.

METHODOLOGY

This section details the methodology used, including software and hardware parts to develop the real-time chickenpox detection system in this work. The software part includes the construction and training of the ResNet-50 deep learning model, while the hardware part implies the implementation of the model using Raspberry Pi for real-time implementation. In addition, the preparation of the dataset and assessment of the model are also involved in the process to guarantee accuracy, speed and usability in clinics.

System Architecture

The software architecture proposed in this work to detect the chickenpox disease is based on the combination of deep learning-based classification and real-time web interface development. In essence, the system employs the Python programming language based on TensorFlow and Keras libraries to train and optimize the deep learning models. In this study, the ResNet-50 model is considered for image classification. Note that the models are assessed based on accuracy, precision, recall and F1-score.

As mentioned earlier, the base model used in this work is ResNet-50 [24] to distinguish the patterns in chickenpox lesion images compared to non-chickenpox counterparts. CNN, widely used for image recognition tasks, includes the pretrained ResNet-50 model, a 50-layer deep learning network trained on one million ImageNet images across 1000 classes [24]. The ResNets were able to solve the problem of vanishing gradients in deep networks by using the Residual Blocks. These blocks used the technique of skip connections [25]. The skip connections help to take a shortcut through some of the layers and connect the activation of the current layers to a layer further ahead. This allows deep networks such as ResNet-50 to learn well without compromising their performance with depth.

After the training process, the RestNet-50 model was uploaded to the Raspberry Pi which was done using Python scripts. Such scripts allowed camera interaction, image capture, and the running of the classification and data

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processing. The front-end part of the system was developed in Visual Studio Code, utilising HTML (Hypertext Markup Language), CSS (Cascading Style Sheets), and PHP to create the system's interface. This interface is used for user verification and to display results. The back end communicates with a MySQL database where the data is stored, and users or doctors can view results via the web app dashboard in a safe manner. This modular and layered software architecture allows the smooth communication between image capture, model inference and visualization of result, achieving an efficient, usable and expandable system to detect chickenpox using images in real time.

Hardware Architecture

The proposed hardware implementation of the chicken pox detection system integrates several essential components for real-time image classification as shown in Figure 1. In this work, a Raspberry Pi 4 is used as the central processing unit of the system. The Raspberry Pi 4 is responsible for executing the trained ResNet-50 model. Also, a USB camera module is integrated with the Raspberry Pi to capture real-time images of facial skin lesions, and these images will be displayed on the 7-inch monitor. To capture the picture, the user needs to press the push button to trigger the process. The colour of the LED will indicate the status of the process, where the yellow goes on when the device is ready to capture a picture, and the green goes on once the image is taken. Once the image has been successfully captured, a buzzer will be triggered, and the classification process will start to classify the image as chickenpox or non-chickenpox using the pre-trained model ResNet-50. The results will be displayed on the monitor and transmitted to a web-based interface wirelessly. Figure 2 shows the working flow of the proposed system.

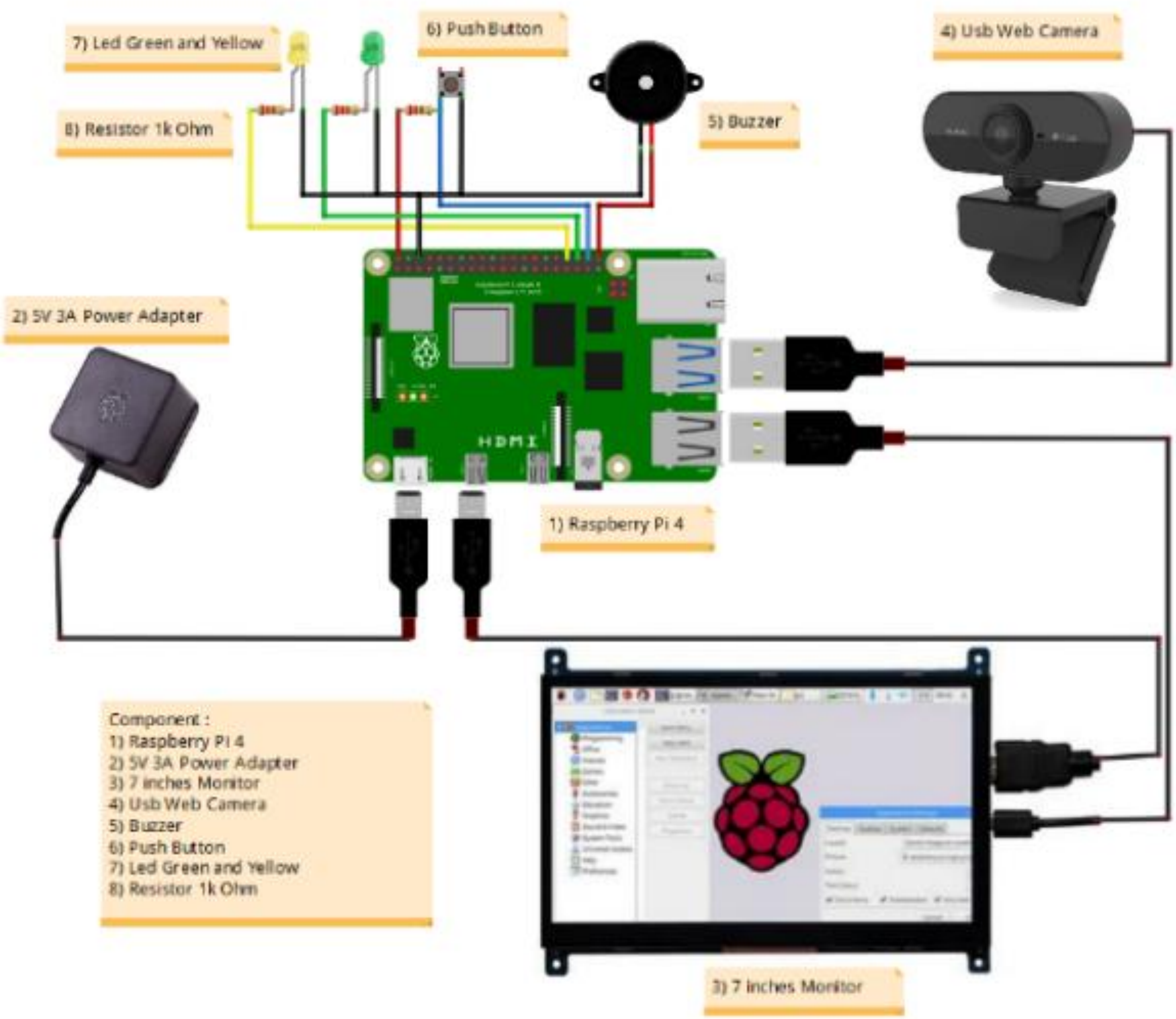

Figure 1. Schematic circuit diagram of the system

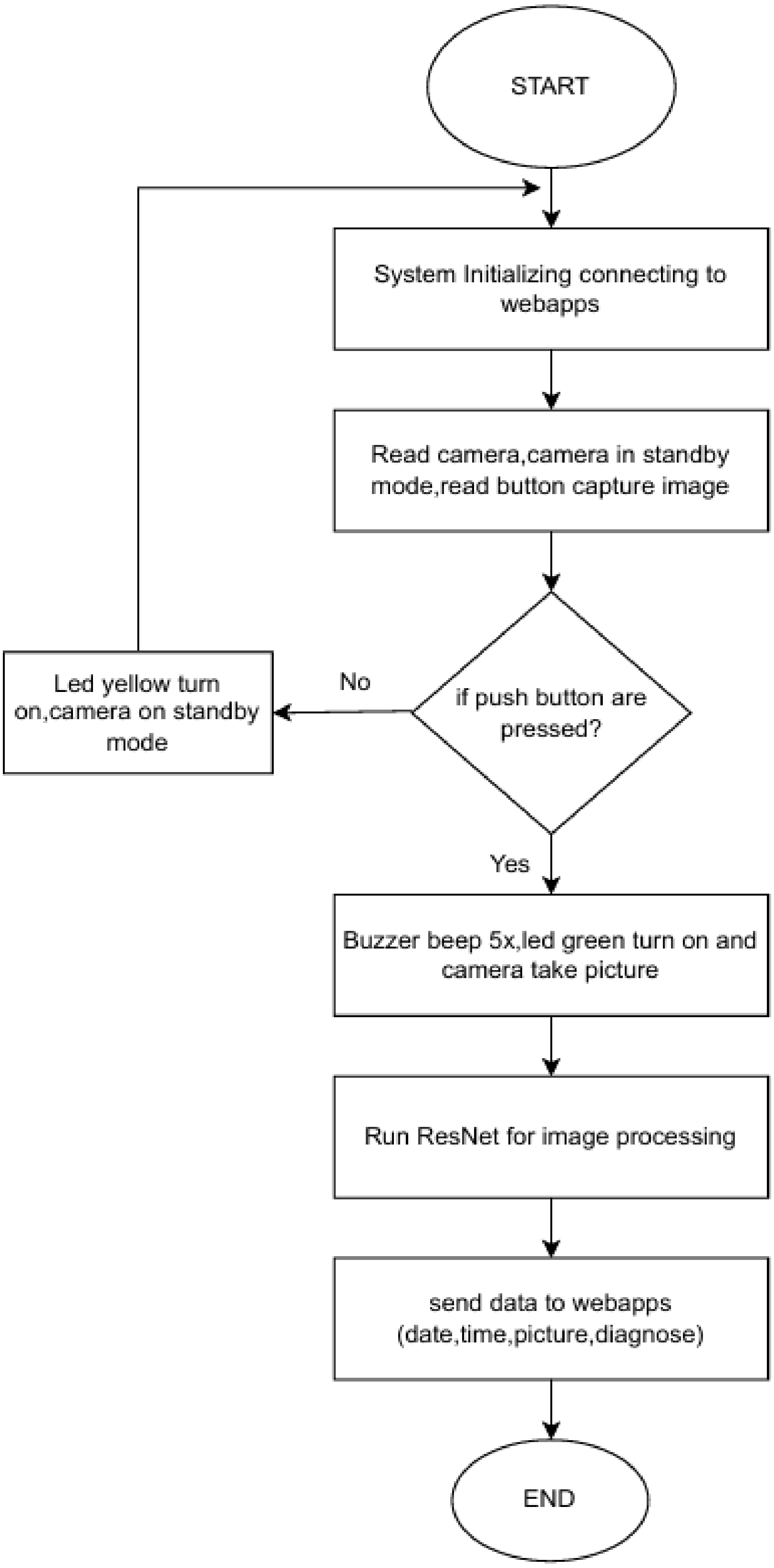

Figure 2. Flowchart of the system

Dataset Preparation

In this work, 1,000 dataset images were utilized, including 500 chickenpox images and 500 non-chickenpox images. The non-chickenpox category is composed of pictures of healthy skin, Hand-Foot-Mouth Disease (HFMD), measles and monkeypox. These pictures were retrieved using publicly available data on the Kaggle website, an online dataset and machine learning resource sharing platform.

The dataset was divided into 800 and 200 images in the ratio of 80:20, set as training and validation, respectively. All the images were transformed to the input parameters of ResNet-50 model. To enhance the robustness of the model and avoid overfitting, data augmentation was performed during training using rotation, zooming, shearing, and horizontal flipping with TensorFlow ImageDataGenerator. Table 1 presents the findings of the images used in training, specifically those depicting chickenpox and non-chickenpox conditions.

Table 1. The dataset sample for the training process

Chickenpox	**Non-chickenpox**			
	Monkey pox	**Measles**	**HFMD**	**Healthy skin**
				

Model Training and Evaluation

The ResNet-50 model was utilised to conduct their training with the frameworks TensorFlow and Keras. 1,000 images were used, with 800 images for training purposes and 200 images for validation purposes. As mentioned earlier, for training purposes, 400 images are chickenpox, while the remaining images are non-chickenpox i.e. HFMD, measles, monkeypox, and healthy skin). Meanwhile, for validation purposes, 100 images are of chickenpox, and the remaining are non-chickenpox, with 25 images per subclass, as follows: HFMD, measles, monkeypox, and healthy skin. All images were re-scaled to 224x224 pixels and were pre-processed by normalization and augmentation procedures; rotation, zooming and horizontal flipping to augment model generalization.

Note that the transfer learning was applied by fine-tuning the pre-trained ResNet-50 model that was trained initially on ImageNet, specifically in the last 30 layers. A custom classification head was included, involving dropout layers and batch normalization to reduce overfitting. The model was trained using the Adam optimiser with a learning rate of 1e-4 and exponential decay. Additionally, the training was supported by callbacks, including EarlyStopping and ModelCheckpoint, which were implemented to retain the best model. For model evaluation, four main metrics were used, including accuracy, precision, recall and F1-score. The results were computed using a confusion matrix. Also, a real-time test was performed to evaluate the performance of the system further.

RESULTS AND DISCUSSION

In this section, the prototype and the web-based application of the proposed system are presented. Note that, these components highlight the successful implementation of the proposed system. Next, the performance of the ResNet-50 model used in the system is given in terms of accuracy, precision, recall and F1-score. Finally, the results of the real-time testing are presented to evaluate the model's effectiveness in a practical environment.

System Architecture and Interface Design

As mentioned in Section 3, the system integrates three main components, including a Raspberry Pi, a web-camera and a monitor. The Raspberry Pi serves as the central processing unit, while the web-camera and monitor are utilized for capturing real-time images and displaying purposes, respectively. Figure 3 shows the prototype of the proposed system.

Figure 3. Prototype of The System

In this work, a web application was developed to enable users and doctors to access prediction results. This web application includes the login process for patient confidentiality. Figure 4 shows the login interface of the proposed system. Meanwhile, Figure 4 and Figure 5 show an example of the dashboard interface of the proposed system. Figure 5 displays the visualization of the confusion matrix that shows the prediction results in terms of percentages. In contrast, Figure 6 shows the classification result indicating whether the case is identified as chickenpox or not, including the captured image.

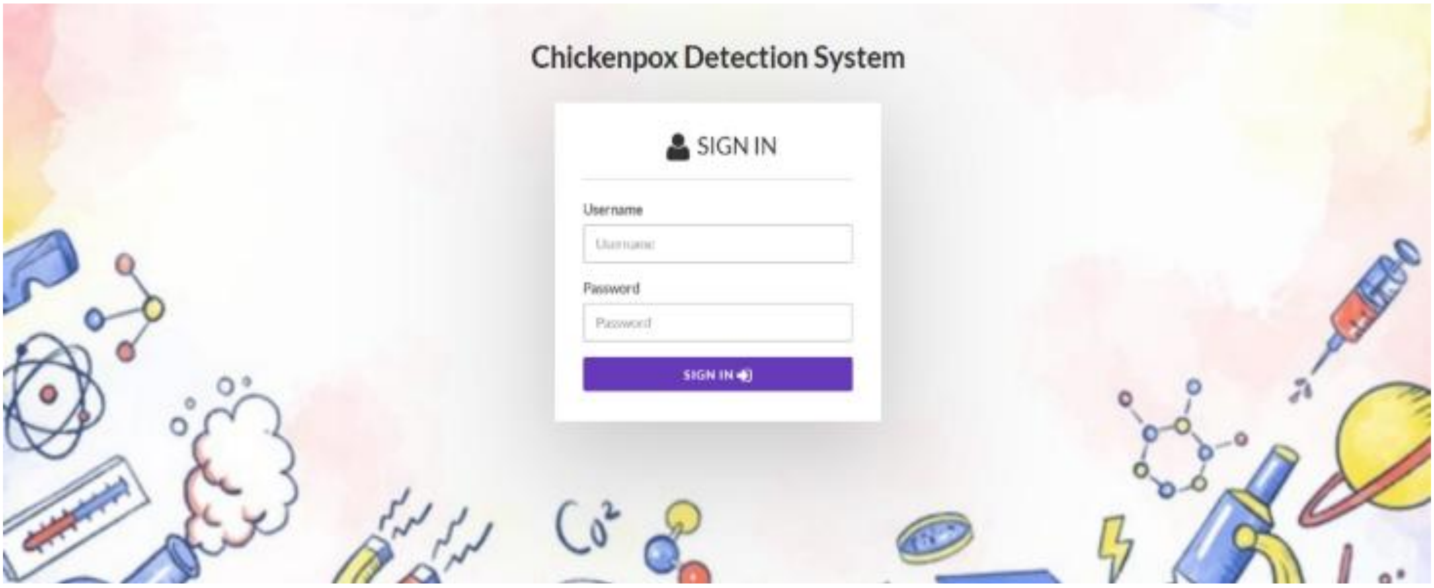

Figure 4. Login Page Web Application

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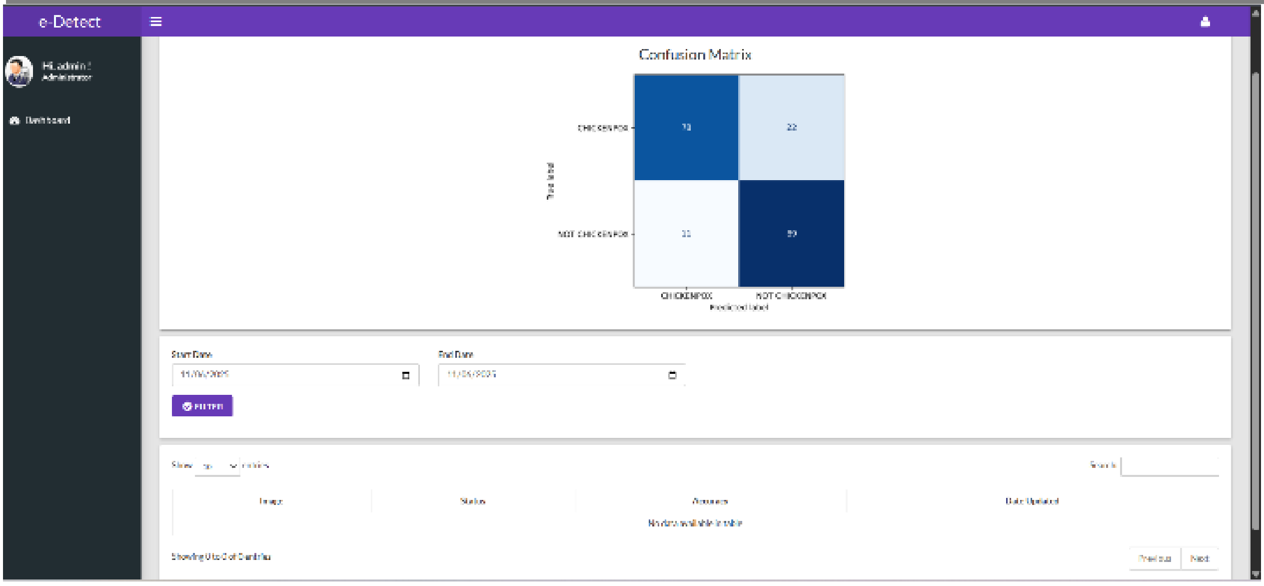

Figure 5. Dashboard interface showing the prediction results using confusion matrix

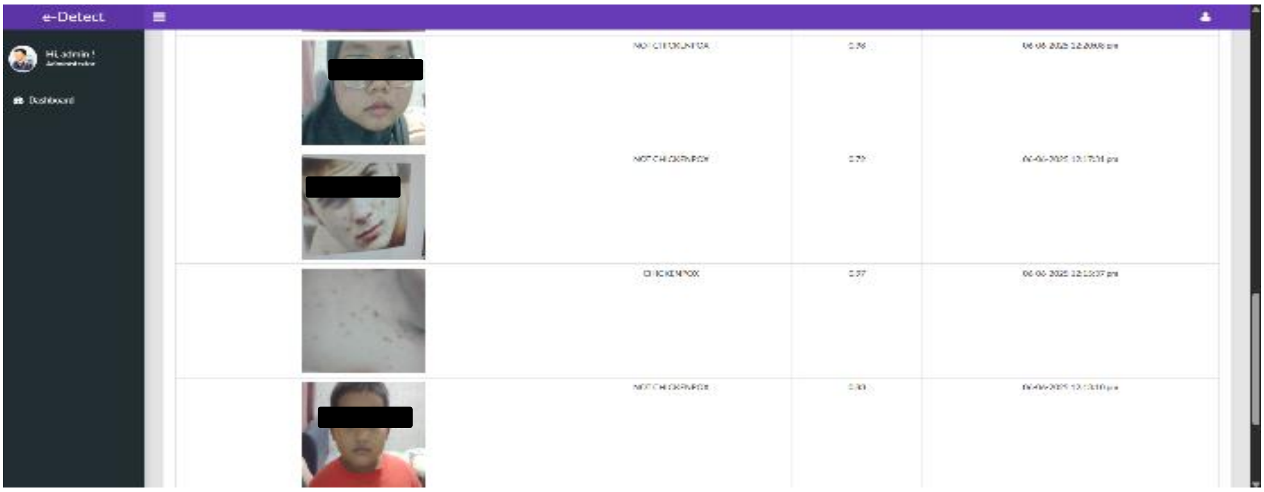

Figure 6. Dashboard interface of the classification result with captured image

Model Performance Evaluation

The confusion matrix is widely used as an evaluation tool to assess the performance of a classification model, especially in binary classification tasks. Therefore, in this work, a confusion matrix is used to evaluate the performance of the proposed system based on the ResNet-50 model. The confusion matrix organizes the prediction model into four main categories as follows:

- TP (True Positive): Predicted chickenpox, and it's correct.
- TN (True Negative): Predicted non-chickenpox, and it's correct.
- FP (False Positive): Predicted chickenpox, but it's not (false alarm).
- FN (False Negative): Predicted non-chickenpox, but it's chickenpox (missed case).

The confusion matrix was used to derive four evaluation metrics for our proposed system as follows:

a) Accuracy: Accuracy is used to show the overall correctness of model predictions, and it is the number of correctly predicted instances divided by the total number of instances [1] as shown in Equation (1):

$$ACCURACY = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

b) Precision: Precision is used to show the number of correct positive predictions that the model makes and is divided by all positive predictions [1] as shown in Equation (2):

$$PRECISON = \frac{TP}{TP + FP} \tag{2}$$

c) Recall: Recall is used to indicate how many times a model predicted correctly when all real cases were positive [1] as shown in Equation (3):

$$RECALL(\,SENSITIVITY) = \frac{TP}{TP + FN} \tag{3}$$

d) F1 Score: F1-score is used to provide a balanced assessment of a model's accuracy when dealing with imbalanced datasets. It is based on the combination of the precision and recall into a single measure by calculating their harmonic mean [18], as shown in Equation (4):

$$F1\ SCORE\ = 2 \times \frac{PRECISION \times\ RECALL}{PRECISION + RECALL} \tag{4}$$

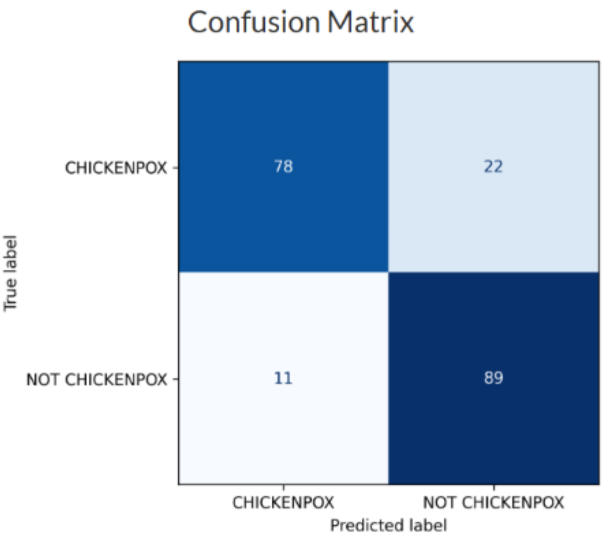

Figure 7. ResNet-50 Confusion Matrix

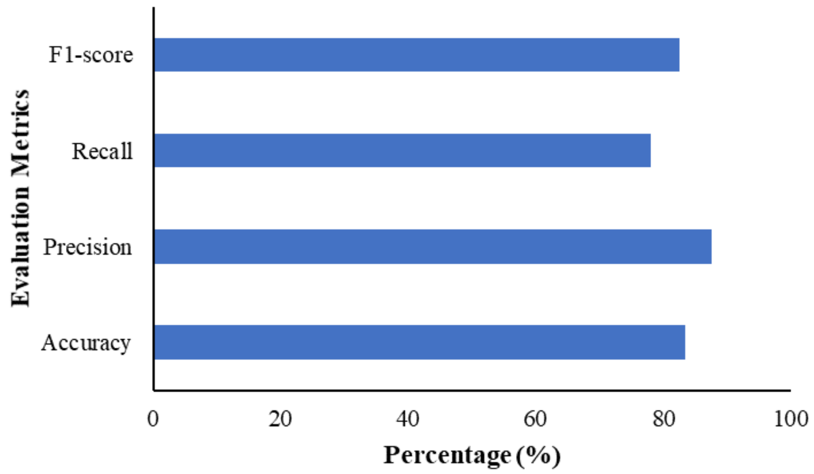

Figure 8. Percentage of the evaluation metrics

Figure 7 shows the confusion matrix results for the proposed system using the ResNet-50 model. The results show that the True Positive, True Negative, False Negative and False Positive are 78, 89, 22, 11, respectively. Based on these values and using equations (1) – (4), the accuracy, precision, recall, and F1-score achieved up to 83.5%, 87.6%, 78.0% and 82.5%, respectively, as shown in Figure 8. This indicates that the model performs well in identifying the chickenpox cases. This is shown by a high precision score, where most of the positive predictions were correct. Besides, based on the recall score of 78%, the model was able to identify correctly a significant portion of actual chickenpox cases, although some cases were missed. However, the high F1-score of 82.5%, which balances precision and recall, confirms the model's overall effectiveness. It is also notable that the high accuracy demonstrates that the model can distinguish between positive and negative cases with good reliability.

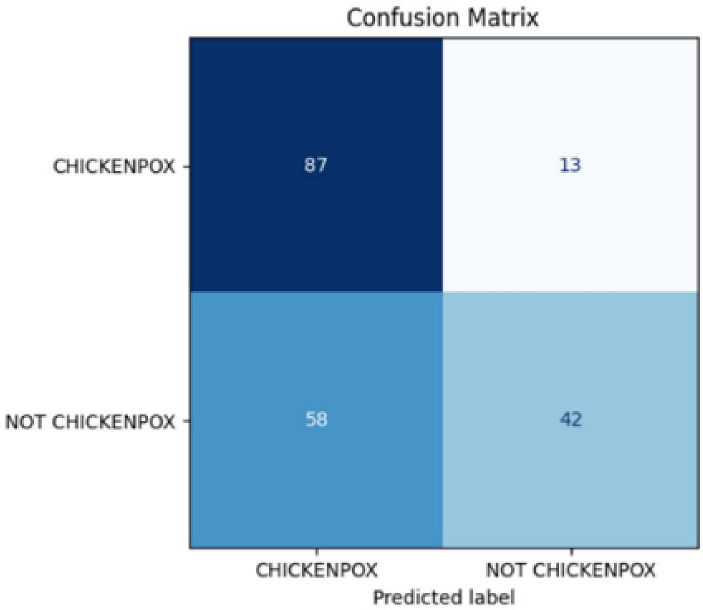

Figure 9. MobileNetV2 Confusion Matrix

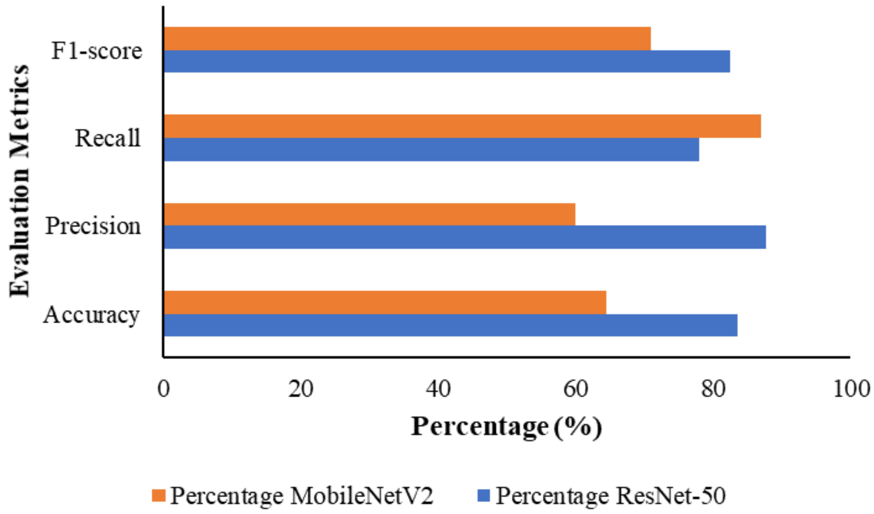

Figure 10. Performance comparison between ResNet-50 and MobileNetV2 models

To further evaluate the efficiency of the ResNet-50 model with our proposed system, we also consider a lighter model, which is MobileNetV2 and use it as a benchmark to evaluate the performance of the ResNet-50 model. We considered the same parameter setting, including the selection and number of datasets as used in ResNet-50 in Section 3. Figure 9 shows the confusion matrix results for the proposed system using the MobileNetV2 model. The results show that the True Positive = 87, True Negative = 42, False Negative = 58 and False Positive = 13. With these values, the accuracy, precision, recall, and F1-score achieved up to 64.5%, 60%, 87% and 71%, respectively, as shown in Figure 10.

The results in Figure 10 also show that MobileNetV2 attained a higher recall value of 87% compared to the ResNet-50 model, which is 78%. However, this improvement in sensitivity was accompanied by a substantial decrease in precision and accuracy, which are 60% and 64.5%, respectively, compared to Restnet-50, which are 87.6% and 83.5%. These results indicate that MobileNetV2 was more capable of identifying positive chickenpox cases. However, it also shows a higher number of false positives. The results also show that the ResNet-50 model exhibited a more balanced performance with 82.5% of F1-score compared to 71.0% for MobileNetV2. This confirmed that ResNet-50 is more efficient in maintaining a trade-off between precision and recall. These features are essential in clinical decision-making scenarios. Therefore, as ResNet-50 offers more consistent and reliable classification outcomes, it is believed to be more suitable for the proposed system.

Real-Time System Testing

In this section, the evaluation performance of the proposed system in real-time system testing was performed using both the RestNet-50 and MobileNetV2 models. Twenty images i.e. 10 images for chickenpox and 10 images for non-chickenpox, were used for the testing of both models. Figure 11 and Figure 12 show the confusion matrix obtained for the testing using ResNet-50 and MobileNetV2 models, respectively.

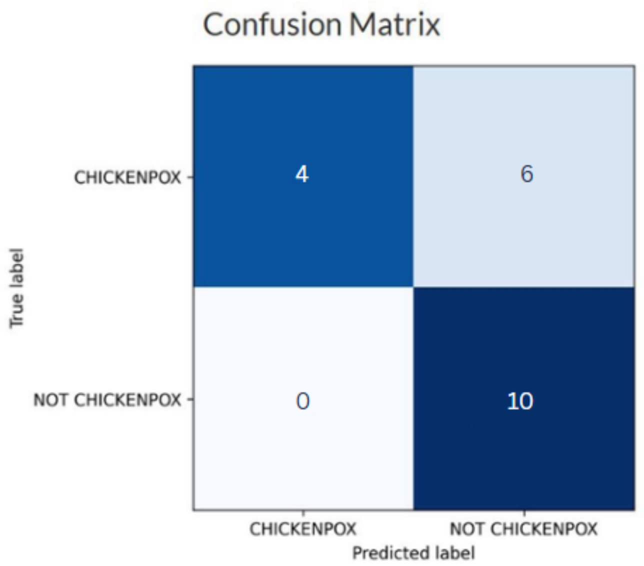

Figure 11. Confusion Matrix for real-time testing using the RestNet-50 model

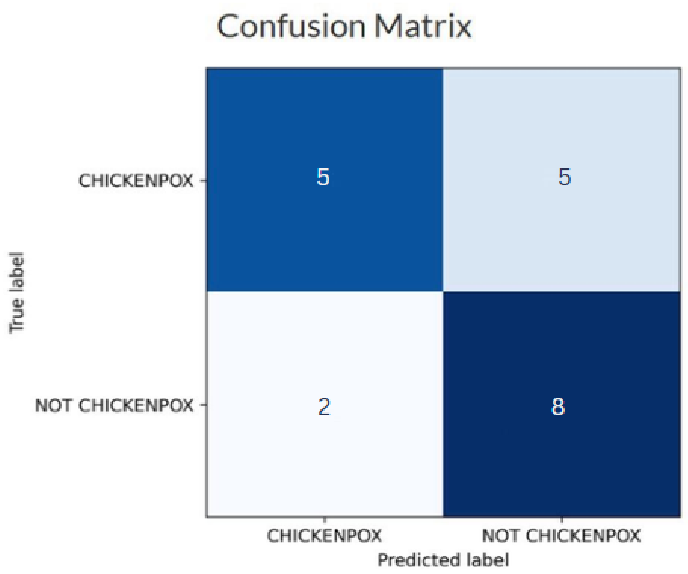

Figure 12. Confusion Matrix for real-time testing using the MobileNetV2 model

Based on the confusion matrix results, in real-time testing, the ResNet-50 model achieved an accuracy of 70%, precision of 100%, recall of 40%, and an F1-score of 57.1%, while for the MobileNetV2 model, achieved an accuracy of 65%, precision of 71.4%, recall of 50%, and an F1-score of 58.8%, as shown in Figure 16. This indicates that, compared to the MobileNetV2 model, the ResNet-50 models has high precision where all positive predictions were correct. However, the low percentage of recall suggested that the model missed several actual cases. Notably, the MobileNetV2 model achieved a slightly better balance between precision and recall. This proved that the ResNet-50 model performed better in avoiding false positives, hence it is more conservative and reliable in reducing false diagnoses. In contrast, the MobieNetV2 model was somewhat more effective in detecting the actual cases but less consistent. Figure 13. Performance evaluation of ResNet-50 and MobileNetV2 models in a real-time environment.

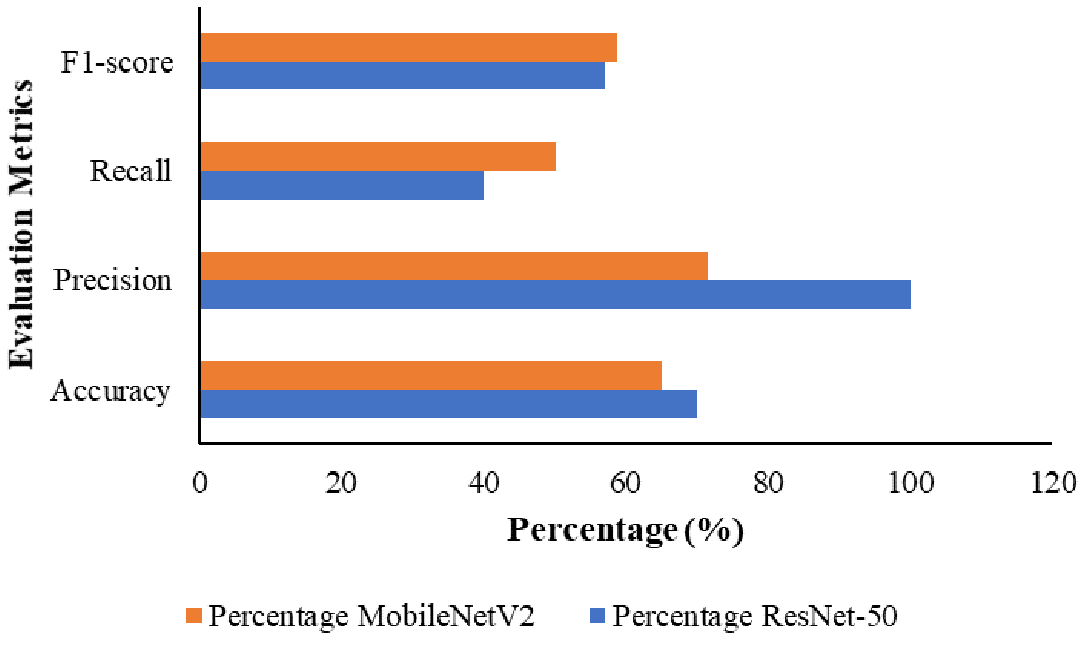

Figure 13. Performance evaluation of ResNet-50 and MobileNetV2 models in a real-time environment

CONCLUSION

This work proposes the development and evaluation of a chickenpox detection system based on image classification using ResNet-50 and MobileNetV2 deep learning models. The proposed system was trained and evaluated using a dataset comprising chickenpox and non-chickenpox images. The results show that the performance of ResNet-50 is much higher compared to the MobileNetV2 model with an accuracy of 83.5%, precision of 87.6%, and F1-score of 82.5%. Meanwhile, the results also show that compared to the ResNet-50 model, the MobileNetV2 model recorded a higher recall of 87.0%. However, the lower precision, i.e. 60.0% and accuracy, i.e. 64.5% of the MobileNetV2 model indicate a higher tendency to generate false positives. In addition, the results of the real-time testing using the developed prototype with 20 images also show that the ResNet-50 model maintained a high precision of 100% but with reduced recall, resulting in a lower F1-score. The results also show that the MobileNetV2 model achieved a more moderate balance with a slightly higher F1-score of 58.8%, but lower accuracy overall. This indicates that although MobileNetV2 demonstrated stronger sensitivity, the ResNet-50 model offered a more balanced and reliable performance. This is particularly important for clinical or screening applications where false positives can lead to unnecessary anxiety or intervention.

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