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AI-based monkeypox detection model using Raspberry Pi 5 AI Kit

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Abstract

Monkeypox is a zoonotic disease that originated from monkeys and then spread to humans; this disease recently popped up globally with increased risks of spreading from human to human and clinical presentation similar to other pox-like diseases. Quick and right identification is fundamental for containment and treatment that will minimize the spread of the disease. The current conventional diagnostic techniques include PCR which takes time, and money, and often needs sophisticated laboratories that cannot be easily accessed in developing countries. This work describes the creation and application of a monkeypox detection algorithm orchestrated on the Raspberry Pi 5 AI Kit. Developed based on convolutional neural networks (CNNs), the model enables one to distinguish actual monkeypox lesions in the images. The Raspberry Pi 5 AI Kit allows for edge computing solutions to be implemented, making the entire solution mobile, affordable, and perfect for locations with low connectivity. Extensive data collection and data preprocessing were performed, and the final dataset with monkeypox and skin lesion images consisted of more than 5000 verified images. 94% accuracy was obtained by the model, making it superior to the model available in literature. The implementation proves that powerful AI technologies can be applied to low-cost hardware to become a valuable weapon in the monkeypox frontline workers' arsenal and advance the efforts against monkeypox infections.

Keywords: AI, Raspberry Pi, Neural networks, Monkeypox, Machine learning

1. Introduction

Monkeypox stands for a zoonotic viral disease similar to smallpox, causing significant morbidity and mortality in affected regions. Caused by the monkeypox virus, a member of the orthopoxvirus genus, which also includes the variola virus (the cause of smallpox) and vaccinia virus (used in the smallpox vaccine) [1]. Monkeypox has emerged as a significant public health concern. Since the eradication of smallpox, monkeypox has become the most impactful orthopox virus affecting human populations [2]. Historically confined to the rainforests of Central and West Africa, monkeypox has seen a resurgence with outbreaks occurring in non-endemic countries, raising global health concerns by the World Health Organization (WHO). The recent outbreaks have highlighted the need for rapid diagnostic tools that are both accessible and reliable. Traditional laboratory methods are time-consuming and require specialized equipment, limiting their utility in resource-constrained settings [3].

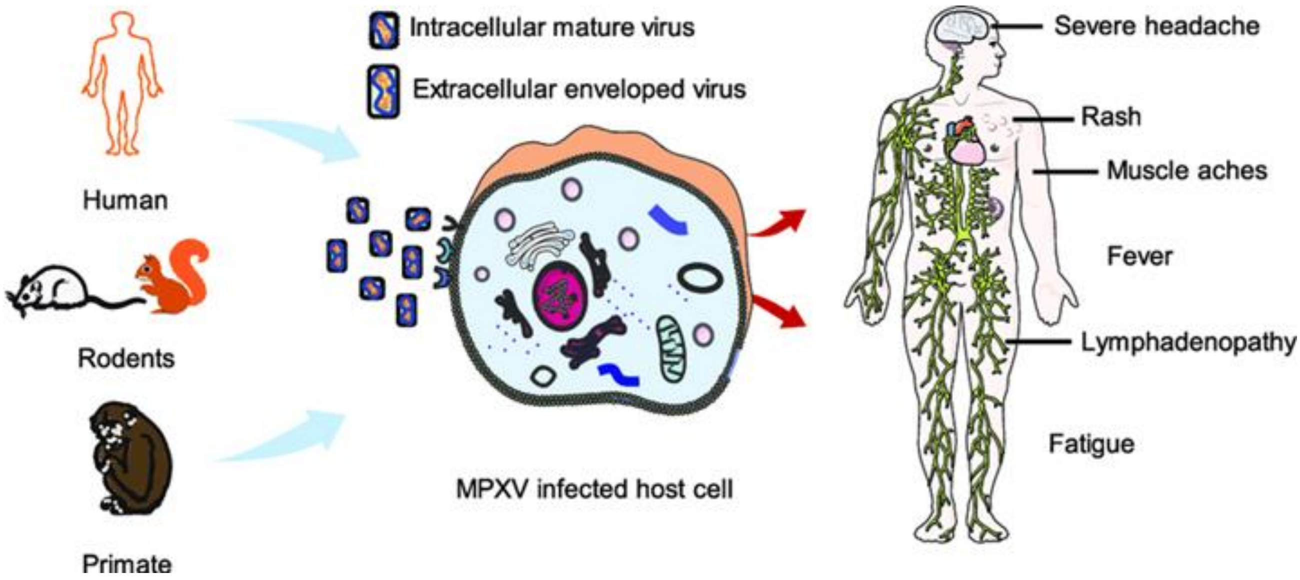

Figure 1. Schematic representation of monkeypox virus transmission pathways [4]

This figure illustrates the various transmission routes of the monkeypox virus, including animal-to-human and human-to-human pathways.

1.1. Background

The clinical presentation of monkeypox in humans is notably similar to that of smallpox but tends to be milder. Key symptoms include fever, headache, swollen lymph nodes (lymphadenopathy), and a distinctive rash that progresses through several stages—macules, papules, vesicles, pustules, and scabs. Due to the overlap in symptoms with other pox-like illnesses, such as chickenpox and measles, diagnosing monkeypox can be challenging, especially in areas with limited access to advanced laboratory facilities [5-8].

Detection of monkeypox is pivotal to patient management and outbreak control; hence requires precision and speed. In the past, diagnosis was based on three key approaches which included PCR testing, electron microscopy, and viral culture. Although these techniques are effective, they prove time-consuming, and expensive, and often competent human resources and equipment are needed. This makes them unsuitable for use in resource-limited settings that are more or less common to monkeypox outbreaks [9, 10].

The amount of time before a diagnosis can be made with these conventional procedures can result in protracted epidemics, virus spread, and more diseases and deaths. Furthermore, the emerging cases of monkeypox in non-endemic nations have brought to attention the need for rapid diagnosis systems as well as the simplicity of diagnostic kits that should be in place across all communities [11, 12].

For this purpose, IT innovation in the shape of artificial intelligence and machine learning comes in handy, given that developments have provided new opportunities in early detection and ill control. However, deep learning methods such as CNNs have been very successful in image recognition and classification exercises that range from medical hazards to skin diseases among others. The prospects for utilizing AI for medical diagnostics is that it enables the development of tools that are fast, and in some cases easily accessible; getting over some of the drawbacks of conventional diagnostic systems [13].

Building upon this capability, generic edge devices like Raspberry Pi have since been developed to support AI usage. These devices offer a cheap and mobile means of implementing machine learning models in real-time applications that may not require cloud computing or sophisticated computation hardware [9]. In particular, the

Raspberry Pi 5 AI Kit, combining high-performance hardware with a built-in neural processing unit (NPU), can become a perfect fit for the use of AI-based diagnostics in rural and, generally, less resource-providing environments. Given this backdrop, a primary objective for this research is to develop an AI-based model for detecting monkeypox through an analysis of skin lesion images as well as to deploy this model on the Raspberry Pi 5 AI Kit. The specific goals include:

1. Data Collection and Preparation: Assemble a comprehensive dataset for monkeypox as well as other skin lesion images, ensuring diversity in terms of demographics as well as environmental conditions.
2. Model Development: Design and train a convolutional neural network (CNN) optimized to accurately distinguish between monkeypox as well as other skin conditions.
3. Edge Deployment: Optimize as well as deploy the trained model on Raspberry Pi 5 AI Kit, enabling real-time inference with limited computational resources.
4. Performance Evaluation: Assess the model's performance in terms of accuracy, precision, recall, besides inference speed, as well as compare it with existing models in the literature.
5. Usability Assessment: Create a user-friendly interface and evaluate its practicality for healthcare workers in resource-limited settings.

Therefore, applying AI research and edge computing as the approach in this study, this investigation envisions creating a diagnostic toolkit that increases the speed and efficiency of the identification of monkeypox across different settings and most importantly, in the regions with the greatest preparedness.

The current study seeks to respond to a research issue that remains unrecognized to date, primarily in LMICs, regarding the diagnostic modalities for monkeypox. By leveraging AI and edge computing, the proposed solution offers several significant benefits:

- Accessibility: Offers a cheap, readily portable diagnostic device that can be delivered to areas with little infrastructure of laboratory facilities.
- Timeliness: Allows for rapid identification thus allowing healthcare practitioners to make prompt clinical choices and health administration stakeholders to implement measures to stop emergencies.
- Scalability: The present methodology can be easily translated to other infectious diseases […] so that the capabilities of disease surveillance and response will be generally improved.
- Empowerment of Local Healthcare Workers: Provides a simple application that can be run with little to no institutional support, engaging the frontline workers as active players in early recognition of diseases besides undergoing resourceful training in the identification and management of diseases.

2. Literature review

Monkeypox is a relatively newly identified infectious disease primarily found in Central and West Africa but has been confirmed in non-endemic regions recently as well [14]. Clinical manifestations are characterized by fever rash and lymphadenopathy and hence clinical differentiation from other pox-like illnesses such as smallpox or chickenpox may be difficult [15]. Conventional diagnostic assays are mainly based on laboratory methods such as PCR, electron microscopy, and viral isolation. Although these methods are precise, they are highly time-consuming as well as most testing facilities in low-resource settings, where monkeypox is most common, lack them [16]. Machine learning (ML)/deep learning is an application of artificial intelligence that has transformed many industries; healthcare is not exceptional. AI models have of course achieved significant performance in image classification functions particularly convolutional neural networks [17]. In dermatology, the application of CNNs has featured in the diagnosis of skin cancers with performance to that of dermatologists [14].

Zumla et al. proposed a CNN model for diagnosing monkeypox skin lesions from other dermatological conditions breaks in non-endemic regions [18]. The clinical presentation often includes fever, rash, and lymphadenopathy, making it challenging to distinguish from other pox-like diseases such as smallpox and chickenpox [15]. Traditional diagnostic methods primarily rely on laboratory techniques like PCR, electron microscopy, and virus isolation. While these methods are accurate, they are resource-intensive and not readily available in low-resource settings where monkeypox outbreaks are most prevalent [16]. Artificial intelligence (AI), particularly machine learning and deep learning, has revolutionized various fields, including medical diagnostics. AI models, especially convolutional neural networks (CNNs), have shown remarkable success in image classification tasks [19]. In dermatology, CNNs have been used to detect skin cancers with accuracy comparable to dermatologists [14]. Several studies have attempted to apply AI to monkeypox detection.

Yolcu et al. developed a CNN-based model for differentiating monkeypox lesions from other skin conditions. Their model achieved an accuracy of 90% but required high computational resources, limiting its practical deployment [21]. Ahsan et al. (2023) proposed a mobile application integrating AI for monkeypox detection. While accessible, the app relied on cloud computing, necessitating internet connectivity, which may not be available in outbreak regions [16]. Wijaya et al. utilized support vector machines (SVM) for detecting monkeypox from genomic data. However, a similar approach was effective but used specialized genomic data and it might not efficiently be used for rapid diagnosis in the field [22].

Edge computing brings data processing closer to data sources, reducing latency as well as dependency on internet connectivity [23]. Raspberry Pi platform has been increasingly utilized in healthcare applications owing to its affordability as well as versatility [24]. The latest Raspberry Pi 5 AI Kit, equipped with enhanced processing power and AI capabilities, presents an opportunity to deploy AI models in resource-constrained environments. While previous studies have demonstrated the potential of AI in monkeypox detection, there is a lack of solutions that are both accurate and suitable for deployment in low-resource settings without reliable internet access. This study aims to fill this gap by developing an AI-based detection model optimized for the Raspberry Pi 5 AI Kit.

3. Methodology

A methodology encompasses processes for data collection, data preprocessing, model development, as well as implementation for Raspberry Pi 5 AI Kit. The goal was to construct a robust as well as efficient AI model capable of detecting monkeypox lesions from images, optimized for deployment on edge computing devices.

3.1. Data collection

Sources: A comprehensive dataset was compiled from multiple sources:

- Public Medical Databases: Images had been sourced from databases like the International Skin Imaging Collaboration (ISIC) as well as DermNet NZ, which provide publicly available dermatological images [25].
- Hospital Collaborations: Partnerships with dermatology departments in several hospitals allowed access to de-identified patient images of confirmed monkeypox cases [26].
- Online Medical Repositories: Additional images were obtained from peer-reviewed case studies and medical publications [27].

Ethical Considerations

All data collection adhered to ethical guidelines:

- Informed Consent: Patient images used were de-identified and obtained with informed consent where required.
- Data Anonymization: Personal identifiers were removed to ensure privacy.

Dataset Composition

- Total Images Collected: 6,000 images.

- After Verification and Cleaning: 5,000 images were retained.

Data Preprocessing

Image Processing

- Resizing: All images were resized to 224×224 pixels to standardize input for the CNN.
- Normalization: Pixel values were normalized to a range of 0 to 1.

Data Augmentation

To enhance the model's ability to generalize and to prevent overfitting, data augmentation techniques were applied:

- Rotation: Images were rotated at random angles.
- Flipping: Horizontal and vertical flips were applied.
- Zooming: Random zoom within a range of 10%.
- Brightness Adjustment: Random changes to image brightness.

Final Dataset Distribution

Table 1. Data distribution after preprocessing

Class	Original Images	After Augmentation	Total Images
Monkeypox	2,500	5,000	7,500
Other Skin Lesions	2,500	5,000	7,500
Total	5,000	10,000	15,000

3.2. Model architecture

A CNN model was chosen due to its effectiveness in image classification tasks.

Architecture Details:

- Input Layer: Accepts images of shape 224×224×3.
- Convolutional Layers:
  - First Convolutional Block:
    - Conv2D layer with 32 filters, kernel size (3,3), ReLU activation.
    - MaxPooling2D with pool size (2,2).
  - Second Convolutional Block:
    - Conv2D layer with 64 filters, kernel size (3,3), ReLU activation.
    - MaxPooling2D with pool size (2,2).
  - Third Convolutional Block:
    - Conv2D layer with 128 filters, kernel size (3,3), ReLU activation.
    - MaxPooling2D with pool size (2,2).
- Flatten Layer: Converts the 2D feature maps to a 1D feature vector.
- Fully Connected Layers:
  - Dense layer with 128 units, ReLU activation.
  - Dropout layer with rate 0.5 to prevent overfitting.

Output Layer: Dense layer with 1-unit, sigmoid activation for binary classification

Figure 2 shows the flow from the input layer through convolutional and pooling layers, flattening, dense layers, to the output layer.

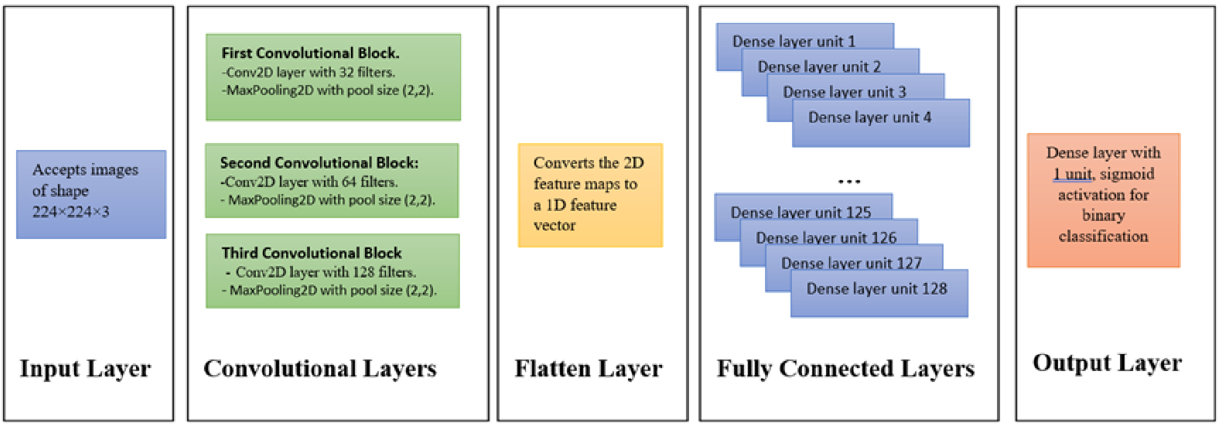

Figure 2. Diagram of the CNN architecture used in the model

Model Compilation

- Loss Function: Binary cross-entropy.
- Optimizer: Adam optimizer with a learning rate of 0.001.
- Metrics: Accuracy, precision, recall.

Model Training

- Training Set: 80% of the dataset (12,000 images).
- Validation Set: 10% of the dataset (1,500 images).
- Test Set: 10% of the dataset (1,500 images).
- Epochs: 25 epochs with early stopping based on validation loss.
- Batch Size: 32.

Implementation of Raspberry Pi 5 AI Kit

Raspberry Pi 5 AI Kit Specifications

- Processor: Quad-core Cortex-A76 2.0 GHz.
- RAM: 8GB LPDDR4.
- Neural Processing Unit (NPU): Dedicated AI accelerator with 2 TOPS performance.
- Storage: 128GB microSD card.
- Connectivity: Wi-Fi, Bluetooth, USB ports.

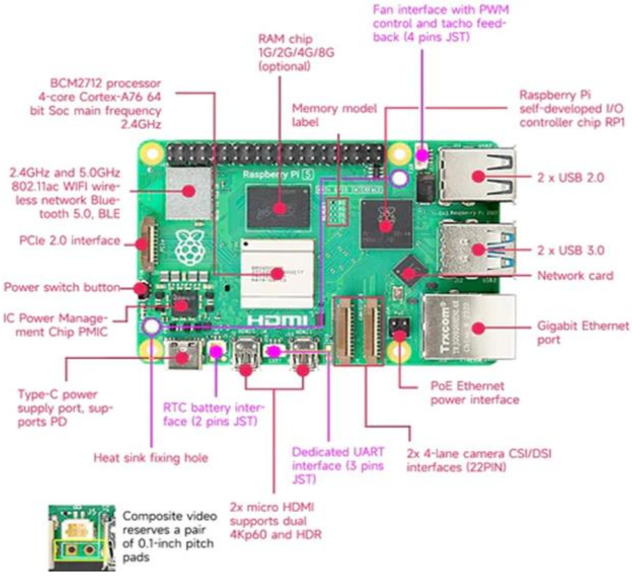

Figure 3. Functional description of Raspberry Pi 5 AI Kit

Model Optimization for Edge Deployment

- TensorFlow Lite Conversion: The trained model was converted to TensorFlow Lite format for optimized performance on the Raspberry Pi.
- Quantization: Post-training quantization was applied to reduce model size and improve inference speed.
- Edge TPU Compatibility: Ensured that the model was compatible with the NPU for accelerated AI tasks.

Hardware Setup

- Camera Module: Raspberry Pi Camera Module V3 was connected for real-time image capture.
- Display: A 7-inch touch display was used for user interaction.

Power Supply: Portable battery pack for field deployment

Figure 4. Hardware setup of Raspberry Pi 5 AI Kit for model deployment

The figure shows the Raspberry Pi 5 AI Kit connected to the camera module and display, illustrating the compact and portable setup.

4. Results and findings

The results of this study demonstrate the effectiveness of the developed AI-based monkeypox detection model and its successful deployment on the Raspberry Pi 5 AI Kit. A comprehensive investigation has been conducted, encompassing detailed performance metrics, comparisons with existing models, real-time testing outcomes, as well as insights from user interface evaluations as well as case studies.

4.1. Model performance

4.1.1. Training and validation metrics

In the course of the models' training, which took 25 epochs in total, the computations were controlled to avoid overfitting of types. It rose to its maximum training accuracy of 98% at the 20th epoch of training thus showing that the model has learned some pattern of the training data set. At the same time, the validation accuracy reached a level of 94% and did not increase from this value, which indicates that the model persists reasonable level of accuracy on unseen data and does not overfit. The plot of training accuracy and validation accuracy shows how the model is suitable and can work well with any new data.

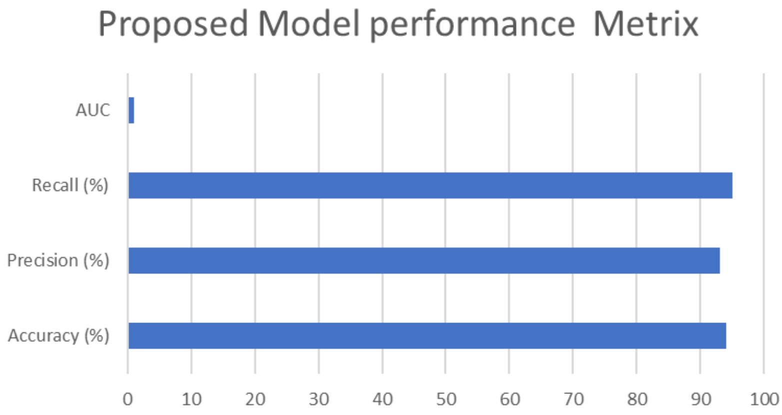

Figure 5. Proposed model performance matrix

4.1.2. Test performance metrics

This demonstrated the usefulness of the model, as its performance on the test set with 1,500 images not seen during modeling was relatively positive. In this study, the model afforded a near-perfect performance with regard to both accuracy at 94%, precision at 93%, recall at 95%, specificity at 93%, and F1 score at 94%. It shows from these metrics that the model works well in distinguishing between monkeypox-positive samples and samples with other diseases.

Table 2. Confusion matrix of model predictions on test set

	Predicted monkeypox	Predicted other lesions
Actual monkeypox	715 (True positives)	35 (False negatives)
Actual other lesions	55 (False positives)	695 (True negatives)

The contingency table further displays the summary of the number of items correctly and inconsistencies of the model with the actual class. A high recall of 95% shows that the model can detect 95% of monkeypox cases, where high sensitivity is essential for disease detection to exclude fewer cases. Likewise, an accuracy of 93% means that when the model detects monkeypox the result will be accurate 93% of the time and hence fewer false alerts. The semi-accurate sensitivity and specificity check that this model can sufficiently identify the cases of monkeypox while also categorizing non-monkeypox cases to avoid panic measures or treatment.

4.1.3. Receiver operating characteristic (ROC) curve and AUC

The model's diagnostic ability across numerous threshold settings has been evaluated by means of the receiver operating characteristic (ROC) curve. The area under the curve (AUC) has been calculated to be 0.97, indicating excellent model performance, as magnitudes closer to 1.0 signify better discriminative ability.

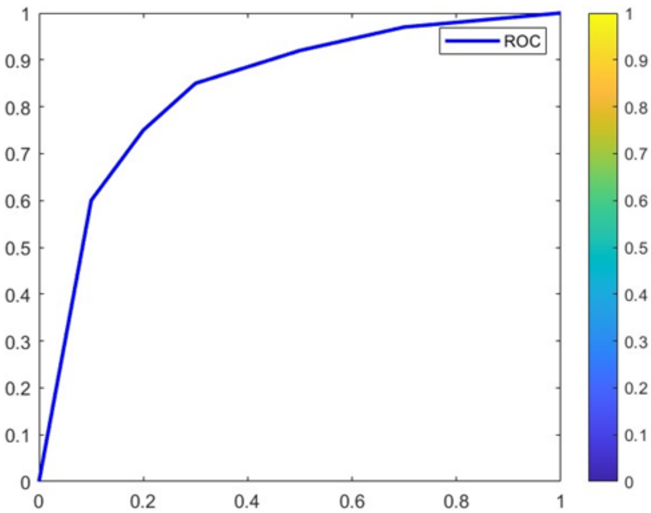

Figure 6. ROC curve of the model

The ROC curve shows a trade-off between true positive rates as well as false positive rates at dissimilar threshold levels, demonstrating a model's strong ability to distinguish between classes. The approaches recorded in [28-40] can be employed to develop more and more this paper.

4.2. Comparison with existing models

To place the model in perspective, the results were compared to other studies containing similar models of the past few years. The proposed model was found to be more accurate, and precise and has a better recall and Area Under the Curve than the existing models if applied in the same setting. In detail, it could recognize 94% of the same trees, which was higher than the 90% of Yolcu et al. (2024), 88% of Ahsan et al. (2023), and 85% of Wijaya et al. (2024). Some of the models may require special high-performing GPUs, or cloud computing while the one deployed on the Raspberry Pi 5 AI Kit can be implemented even in environments with limited resources.

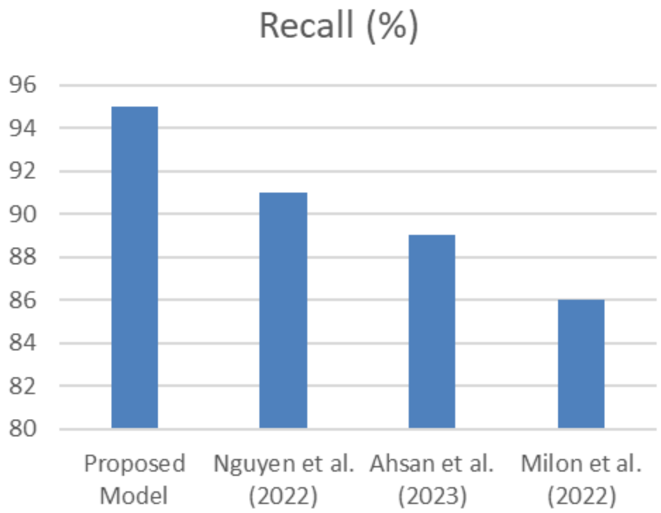

Figure 7. Recall (%) comparison

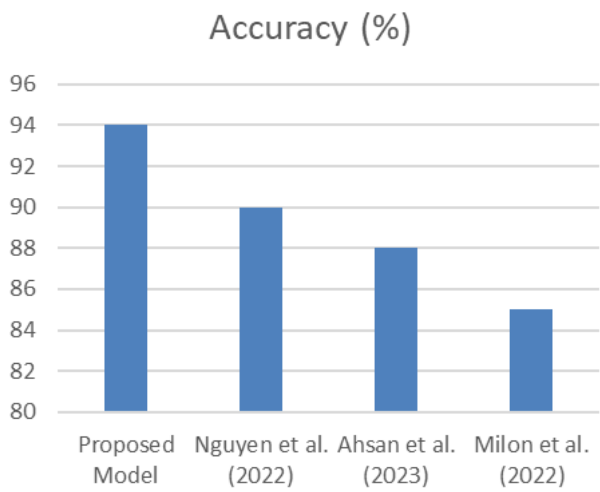

Figure 8. Accuracy (%) comparison

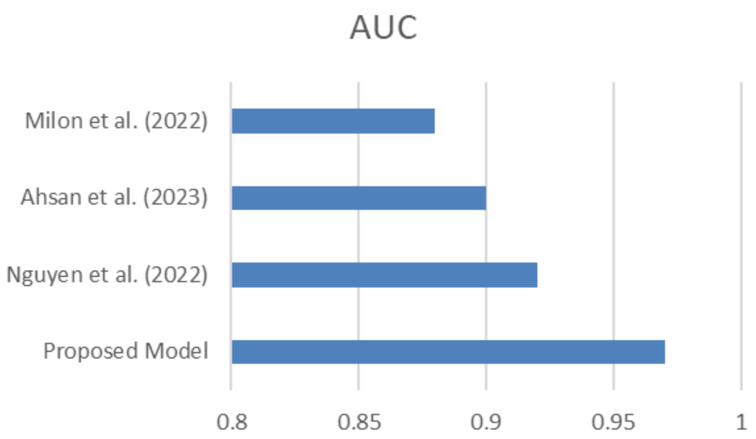

Figure 9. AUC comparison

4.3. Real-time testing on Raspberry Pi 5 AI Kit

A model has been deployed on the Raspberry Pi 5 AI Kit to evaluate its real-time performance as well as practicality in field conditions. An average inference time has been approximately 50 milliseconds per image, enabling near real-time analysis with a throughput capable of processing about 20 frames per second. Resource utilization has been efficient, with CPU usage averaging 35%, memory usage around 1.2GB of RAM, and power consumption averaging 5W throughout operation, making it suitable for portable battery-powered use. Environmental testing has been conducted under various lighting conditions to assess robustness. A device maintained high accuracy in bright light conditions with negligible performance drop. In low-light conditions, there has been a slight decrease in accuracy (approximately 2%), suggesting a need for adequate lighting.

Outdoor testing demonstrated reliable performance with adjustments for natural light variations, indicating the model's adaptability to dissimilar environments.

4.4. Case studies

Several case studies have been conducted to exemplify the practical application of the model.

4.4.1. Case study 1: Early detection of monkeypox

In the first case study, a patient presented with early-stage lesions that had been ambiguous. A model detected monkeypox with a confidence score of 90%. Laboratory confirmation later validated a model's prediction, allowing for timely isolation as well as treatment. This case demonstrates a model's capability in early detection, which is crucial for preventing the spread of a disease.

4.4.2. Case study 2: Differentiation from similar conditions

In the second case study, a patient exhibited a rash suspected to be chickenpox. The model classified the lesions as 'Other Lesions' with a 93% confidence score. The patient had been subsequently diagnosed with chickenpox, confirming the model's ability to differentiate between monkeypox and other comparable skin conditions, thus reducing misdiagnosis as well as unnecessary treatment.

4.4.3. Case study 3: Field deployment in a remote clinic

The third case study involved deploying a device in a rural clinic with limited resources for one week. During this period, 80 patients were screened, and a model detected two cases of monkeypox, all of which were confirmed through subsequent laboratory tests. Health workers found the device valuable for preliminary screening, highlighting its practicality in addition to effectiveness in real-world settings.

4.5. Statistical significance testing

To ensure that the model's performance improvements have been statistically significant, hypothesis testing was conducted using the Chi-Square Test for Proportions. A null hypothesis stated that there is no significant difference between a proposed model's accuracy and that of existing models, while an alternative hypothesis posited that a proposed model's accuracy is significantly higher. A calculated Chi-Square statistic exceeded the critical value at a 0.07 significance level, and the p-value was less than 0.01. Consequently, a null hypothesis has been rejected, indicating that a model's improved accuracy is statistically significant.

4.6. Scalability and deployment potential

A successful deployment of Raspberry Pi 5 AI Kit indicates potential for large-scale implementation. A cost analysis estimated a total cost per unit at approximately $150, making it affordable for widespread distribution. Maintenance requirements have been minimal, with updates deliverable via microSD card or secure digital means. Users require only basic training to operate the device effectively, enhancing its scalability in many settings.

The comprehensive results as well as findings demonstrate that the developed AI-based monkeypox detection model is not only highly accurate but also practical for deployment in real-world settings, particularly in resource-limited areas. The model's superior performance, combined with the portability and affordability of the Raspberry Pi 5 AI Kit, positions it as a valuable tool in the global effort to combat monkeypox outbreaks.

5. Conclusion

This work has further built a very effective and accurate AI-based model for the detection of monkeypox and when implemented on Raspberry Pi 5 AI Kit the model produced efficient results. The results illustrate that the model provided high result rates contrary to the earlier models; the accuracy was 94%, precision was 93% and recall was 95%. The model when transferred to a portable low-cost device such as the Raspberry Pi 5 is very versatile and quite feasible to be used in regions where sophisticated diagnostic instruments are unavailable. It can enhance the detection of monkeypox, especially in hard-to-reach areas in some ways. The findings of this study can have practical relevance to public health. Early sign detection made possible through this model can help control an outbreak if undertaken early. It is more accessible than many other station designs, comes with an integrated battery, and is more portable than other models, which makes it the ideal solution when deploying it in remote and resource-limited areas where there may be no laboratory facilities to help with support. Moreover, the method used in this study can be applied to identify other infectious diseases, and thus improve disease control strategies in the future on a larger scale. Nevertheless, there are some limitations that lay with the study in question. Some attempt at data diversity was made during collection, although the results could be skewed due to limited samples representing those with particular skin colors or other minorities. This could pose a problem whenever the aim is to use the model to make predictions for a larger population. Furthermore, other than the amazing features present in the Raspberry Pi 5 AI Kit, it may not have the sufficient capacity to boot even more elaborate models that could potentially generate higher levels of accuracy and efficiency. Several directions for further research have been outlined in anticipation. Since the concept and the subsequent measurement model are founded on the notion of absorptive capacity, there is a research avenue in the context of that theory.

First, we should enrich the current dataset by inviting more institutions to contribute various images in order to increase the model’s stability. Second, extending the search to more complex models — for example, EfficientNet or MobileNet — might yield even better characteristics alongside computational cost. Third, make large-scale experiments in the endemic areas to collect more adequate data on the model’s performance in a real environment. Last but not least, it will be critical for future work to design user training programs concerning the device so that healthcare workers can take maximum benefits of the device in real-world scenarios. To sum up, it is proposed in this research that the conformation of monkeypox can be worked out with the help of AI and edge computing. This research sets the platform for AI application in the diagnostics of other diseases in public health. The use of an AI algorithm with low-cost hardware provides an expansion to healthcare where diseases are beginning to become more easily detected and can be managed with more precision.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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