MobileNet Neural Network skin disease detector with Raspberry pi Integrated to Telegram

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Abstract

Skin diseases with their malignant Melanoma and benign Keratosis are two major global health issues that affect people around the world. The timely identification of skin diseases remains essential for qualified medical treatment which delivers better results to patients. The absence of available clinical diagnosis tools results in prolonged medical examinations and elevated death counts among patients. A complete system for skin disease detection presents an integration of MobileNet Convolutional Neural Network (CNN) detection and Raspberry Pi and Telegram realtime monitoring capabilities and notification functions. The MobileNet CNN operates with a lightweight structure that employs Depthwise Separable Convolution to reach processing complexity reduction rates of 8-9 times lower than those of standard convolutional networks. This implementation enables skin lesion classification through transfer learning which re-trains a MobileNet model that already exists for skin lesion specialization. The system provides precise and reliable predictions that achieve validation accuracy of 0.96 for top-3 results and 0.89 for top2 performance when it categorizes skin lesions into Melanoma and Benign Keratosis classes. The Raspberry Pi enables local image processing operations which allows for a budget-friendly system deployment in areas with limited resources. The real-time notification system along with classification outcomes reaches both users and healthcare personnel through Telegram to provide them with quick access to medical assessment. Through this integrated approach detection becomes more efficient at the same time it provides improved accessibility. The proposed detection system provides a strong and budget-friendly technology solution which scales for early skin disease diagnoses worldwide. The future *development of the system will focus on expanding the available dataset for better accuracy as well as adding more diagnostic elements that will result in complete skin health evaluation.*

Keywords: MobileNet CNN, Raspberry Pi, Telegram Integration, Skin Disease Detection, Skin Lesion Classification, Depth wise Separable Convolution, Melanoma, Healthcare Technology.

Introduction

People of all ages are affected by skin diseases which stand among the leading global health issues. Medical experts must diagnose these conditions earlier because proper treatment demands this step. Traditional diagnosing methods depend on specialist medical tools combined with dermatological knowledge but these resources prove difficult to access mainly in outlying and underprivileged regions. The study presents a MobileNet Neural Network-based skin disease detection system which integrates with Telegram and operates through a Raspberry Pi device. This system delivers a budget-friendly approach to diagnose skin diseases through combination of image processing solutions with deep learning applications. The MobileNet model delivers effective skin lesion classification while using small computational resources.

The project seeks to achieve three main targets: first it aims to develop an effective light-weight neural network based on MobileNet and second it aims to integrate this neural network with Telegram for hassle-free image submission and result retrieval and third it aims to deploy this system through Raspberry Pi for low-cost portability. The solution delivers special advantages to areas without proper dermatological service access because it allows users to get early skin disease diagnosis while enabling prompt medical intervention.

The traditional method for diagnosing skin cancer has relied on dermatologist manual examinations since several decades. This diagnosis method proves effective yet it encounters difficulties because skin disease cases are increasing rapidly. Patients face delays in detecting their condition as well as inadequate treatment results because of insufficient medical facilities combined with high expert diagnostic expenses. Melanoma skin cancer stands as one of the primary cancers worldwide while early diagnosis promotes the highest chances of recovery. Scientific research demonstrates that patients diagnosed at an early stage achieve a 97% survival rate.

Visual assessments with ABCDE evaluation remain standard practice although doctors use them across medical facilities. Specialized medical personnel are required for these techniques to operate because they remain susceptible to human mistakes when used alone. Artificial intelligence technology has generated automated diagnostic systems giving hopeful results although several existing systems prove expensive or demand heavy computation power while being scarce in distribution.

This project handles these complex issues by establishing MobileNet CNN together with Depth wise Separable Convolution to decrease computational requirements. The model design achieves efficient Raspberry Pi operation with its capacity to maintain high classification accuracy. The integration of Telegram enables real-time communication that delivers immediate results to patients and speeds up their access to medical consultation services.

Overall, the proposed system presents an innovative and practical approach to skin disease detection, bridging the gap between medical expertise and communities with limited healthcare access. It offers a scalable and cost-effective solution that has the potential to significantly improve early diagnosis rates and enhance patient outcomes.

Related Works

Several studies have highlighted the significance of early diagnosis in skin cancer and the role of advanced technologies in aiding the detection process.

L.A. Torre et al. [1] provided a comprehensive analysis of global cancer statistics, emphasizing the prevalence of skin cancer and the importance of early detection. This study underscores the need for accessible diagnostic tools like the proposed MobileNet-based system.

E. Nasr-Esfabani et al. [2] demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in analyzing clinical images for melanoma detection. Their research supports the use of CNNs for accurate medical image classification, forming a foundation for this project.

J. Rathod et al. [3] applied CNN models for diagnosing skin diseases, proving their capability to offer high accuracy in classification. This study aligns with the project's objective of using MobileNet CNN for lightweight and efficient skin lesion classification.

A. Candra et al. [4] evaluated the security aspects of Telegram as a communication platform. Their analysis ensures confidence in the integration of Telegram for secure real-time notifications in the proposed system.

G. Schaefer et al. [5] investigated image overlay techniques using thermal and visual images for skin detection. While not directly applied in this project, their insights into image processing remain relevant for future improvements.

C. L. Aruta et al. [6] presented a mobile-based medical assistance system for diagnosing skin diseases. Their use of mobile platforms for accessible healthcare services is aligned with the current project's use of Raspberry Pi for portable and low-cost diagnosis.

A. C. Amarathunga et al. [7] developed an expert system for skin disease diagnosis using rule based methodologies. Although effective, expert systems lack the adaptability of CNN models, further validating the decision to use MobileNet CNN in this study.

O. B. Akinrinade et al. [8] utilized graph-cut techniques for melanoma segmentation across different color spaces. While the current project focuses on classification rather than segmentation, such approaches could be beneficial for future enhancements.

P. Tschandl et al. [9] introduced the HAM10000 dataset, consisting of dermatoscopic images for common skin lesions. This widely used dataset forms the basis for training and validating the MobileNet model in this study.

D. B. Mendes and N. C. Silva [10] applied CNNs for skin lesion classification using clinical images. Their research demonstrated CNNs' effectiveness in medical diagnosis, supporting the implementation of MobileNet CNN for accurate predictions.

J. Rathod et al. [11] further contributed to skin disease diagnosis using CNN models. Their findings reinforce the reliability of CNN-based approaches in identifying skin conditions, complementing the goals of this study.

Z. Y. Ge et al. [12] explored the enhancement of image classification using local deep CNN features. Incorporating such techniques into MobileNet CNN could improve the accuracy and robustness of the system.

F. Saeed et al. [13] demonstrated CNN-based early fire detection using real-time image processing. While the context differs, their approach showcases the effectiveness of CNNs in detecting anomalies, which is applicable in medical image analysis.

J. Alzubi et al. [14] provided a broad overview of machine learning algorithms and their applications. Their insights contribute to the theoretical framework of this study, reinforcing the rationale behind choosing CNNs for image classification.

J. C. Oliveira et al. [15] introduced the use of Telegram bots for communication with Arduino platforms. Their work validates Telegram's capability as a reliable medium for real-time notifications, an essential component of the proposed skin disease detection system.

These related works collectively establish the foundation for developing an accessible, efficient, and accurate skin disease detection module using MobileNet CNN, Raspberry Pi, and Telegram integration.

Methodology

A well-defined methodology directs the proposed skin disease detection system to classify accurately while providing a smooth communication channel to users. The methodology contains important steps which begin with image acquisition and move to preprocessing then model training followed by Raspberry Pi deployment and Telegram bot integration. Each step is elaborated below in figure 1.

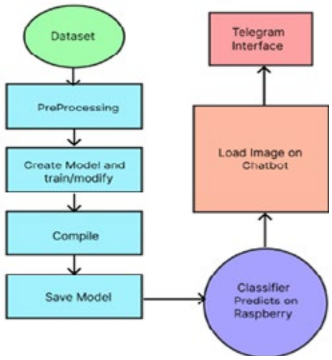

Figure 1. Block Diagram of Mobile Net Neural Network skin disease detector

Image Acquisition

People who use this system will take pictures of these suspected skin lesions through both smartphone cameras and digital photographic devices. The wide availability of smartphones facilitates the approach to enable remote participation since participants do not need medical equipment. Users who want to submit their images should use a Telegram bot which offers a straightforward user interface to perform uploads. Users can depend on Telegram's image sending platform which provides them with secure fast image delivery. Users can depend on real-time engagement through the platform that enables immediate feedback distribution.

Smartphones used to capture images create both easier accessibility to healthcare and lower total diagnostic expenses. Users gain privacy protection because Telegram implements an encrypted system to securely send medical images using its messaging platform.

Image Preprocessing

The received images require preprocessing treatment before they can achieve compatibility with the MobileNet model. The correct classification requires effective preprocessing which consists of multiple critical operations:

- The image processing starts with resizing all images to 224x224 pixels for compliance with MobileNet's minimum input needs. Data consistency exists because all dimensions maintain equal metrics.
- The dataset preserves images in RGB format instead of converting them to grayscale. The presence of different skin lesion colors matters greatly because these colors help identify particular skin conditions.
- The normalization process adjusts pixel values into the range of [0,1] because it enables more efficient model training and prediction. Images with different exposure values play equally well under normalization procedures.
- Basic image filtering techniques will minimize noise present from both low-light photographs and poor camera quality. The processed images will become clearer after applying Gaussian blur or median filtering techniques.

MobileNet Model Implementation

The lightweight nature of the MobileNet model together with its low computational complexity makes it the main detection core. MobileNet offers optimal performance for embedded and mobile applications primarily because it was built for those devices such as Raspberry Pi. The main innovative element of MobileNet involves Depth wise Separable Convolution while maintaining accuracy levels.

- The depth wise convolution operation uses a single filter to scan through input channels independently. The computation requires fewer operations in this method than conventional convolution operations.
- A sequence of depth wise convolution follows with 1x1 convolutions for merging the output channels. The step adds another stage of computation reduction.

The combined operation speeds of these methods allow MobileNet to function up to 8-10 times faster than standard CNNs thus making it practical for real-time processing.

Transfer Learning and Fine-tuning

- Transfer learning will be used to increase accuracy levels of the model. The application adopts MobileNet and utilizes its pre-learned model trained on large image sets then applies further optimization to detect skin diseases.
- The convolutional layer components of MobileNet function as feature extraction elements while staying intact for this task. The visual patterns learned by this layer system enhance the capability for identifying different skin diseases.
- Specific layers of the model will be made trainable again for retraining on HAM10000 despite keeping the rest of the layers frozen during this process. By using fine-tuning the model becomes capable of learning distinct features that specifically pertain to skin tissue therefore improving its diagnostic performance.
- Additional fully connected layers will be added after the structure adaptation to help the model distinguish various skin diseases in the classification task.

Model Training

High accuracy from the training process can be achieved through appropriate data management and model optimization methods. The collected dataset will split into three parts for training, validation, and testing uses.

- Different augmentation techniques including image rotation along with flipping and zooming and brightness adjustments will enhance the model's generalizability through creation of a diverse dataset.
- The Adam optimizer will function as an adaptive learning rate controller to efficiently find the minimum of the loss function during optimization.
- The model performance will be measured through evaluation metrics which consist of accuracy alongside precision and recall and F1-score scores. The framework includes metrics that lead to accurate discrimination for all skin disease types.
- The model's performance will reach its best potential through careful regulation of number of epochs in combination with batch size selection. A compromise will be established between training speed and accuracy when selecting the number of epochs and batch size.

Deployment on Raspberry Pi

The MobileNet model receives deployment on a Raspberry Pi for the purpose of running real-time process applications on minimal computing infrastructure. Affordability and accessibility of

Raspberry Pi lead it to become an optimum choice when developing budget-friendly diagnostic systems. Key steps in deployment include:

- The conversion of MobileNet into an optimized format for Raspberry Pi purpose will utilize TensorFlow Lite functions.
- The optimized model will use a Python-based inference engine as part of a complete system to process images for real-time classification results.
- A combination of efficient memory management techniques ensures smooth operation of Raspberry Pi due to its hardware limitations.

Telegram Bot Development

The proposed system will use a Telegram bot for its user interface component. The proposed system uses the Python Telegram API to operate between terminal interfaces and control both user communication and image data transmission and predictive functions.

- Users will transfer images for examination through the bot platform.
- Results of classification will be provided by the bot together with confidence levels. The system will deliver vital information regarding the diagnosed skin disease to its users.
- The bot provides extended resources and doctor referral recommendations to users for detailed guidance.

Evaluation

Several evaluation criteria will determine the success of the proposed system.:

- The model's accuracy will be determined by comparing its output to original label data through the accuracy metric.
- The system will track the complete time period from image upload until receiving classification outcomes to verify real-time operation.
- User Experience Assessments will come from surveys that measure system usability and satisfaction levels of end-users. Continuous feedback serves to enable multiple performance updates.

The systematic method leads to the creation of an accurate user-friendly skin disease detection system through the integration of MobileNet CNN, Raspberry Pi, and Telegram.

Results and Evaluation

The evaluation of the proposed skin disease detection system uses MobileNet Convolutional Neural Network (CNN) on Raspberry Pi and integrates with Telegram for real-time monitoring. The performance evaluation examines essential performance measures which encompass accuracy loss reduction as well as classification performance system usability alongside real-world response time metrics.

Model Training and Evaluation

A MobileNet CNN performs training through utilization of the HAM10000 dataset or similar labeled datasets which contain various skin lesion images. A performance evaluation of the model relied on measuring accuracy rates and loss values obtained from training and validation datasets.

Training showed continuous progress toward accuracy enhancement while loss values progressively decreased thus demonstrating the development of effective learning. The model demonstrated increasing validity in its predictions which validated its capacity to analyze new cases.

Key Training Metrics

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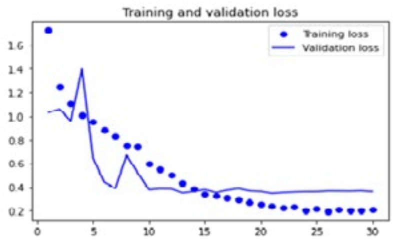
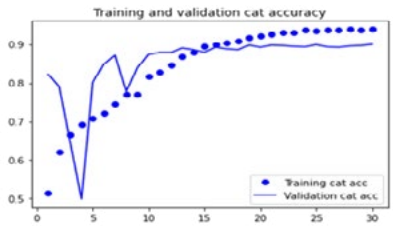
Performance Trends Over Epochs

- During the training's early phases, the model efficiently acquired primary skin lesion characteristics which produced quick accuracy gains.
- The training accuracy corresponded very closely with the validation accuracy which showed that overfitting remained at a minimum level.
- The Depth wise Separable Convolutions in MobileNet achieved better performance with reduced computational requirements.





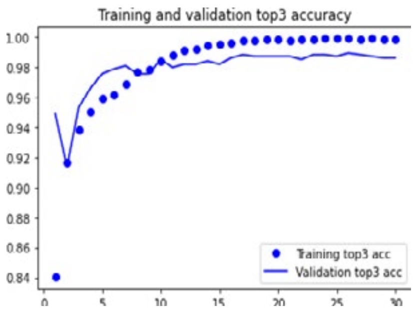
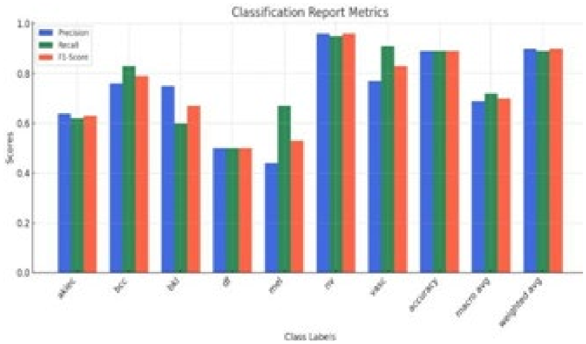


Table 1 Comparison of Training Top-2 with Training Top-3 Accuracy and Loss(%) for 3 Epochs

No. of Epoch	Training Top-2 Accuracy (%)	Training Top-3 Accuracy (%)	Training Loss (%)
1	85	86	1.8
2	88	93	1.0
3	90	95	0.8



Visual Representation of Results

The model performance was displayed through accuracy and loss trend graphics to make its performance more evident. The visual representations of model performance demonstrated both stability and efficient learning abilities of the model.

Observations from Graphs

- Accuracy Curves revealed a stable upward pattern with small variations which indicated stable training process.
- The training and validation loss decreased substantially throughout the process which demonstrated successful learning.
- The model reached convergence during its tenth epoch thus establishing MobileNet as an appropriate system for skin lesion classification given in the figure 2.

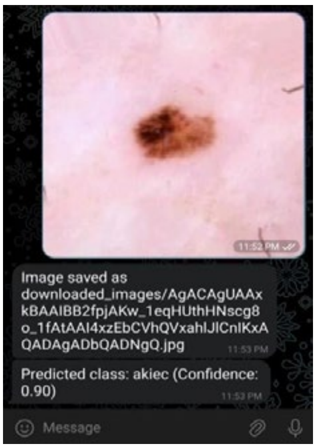


Figure 2 Output Results on Telegram

Real-Time Prediction and Response Time

After deploying the system onto Raspberry Pi the evaluation of its real-time operation included analyzing the Telegram bot functionality. The model exhibited:

- Fast prediction times, with results generated within 2-3 seconds after image submission.
- Telegram's lightweight messaging infrastructure ensured instant classification updates. Users received:
- Determines medical issues through predictions that include confidence scores for each recognition along with extra disease-relevant information.
- The solution includes extra disease-specific content that outlines the need to seek dermatologist guidance.

Evaluation Metrics

Standard performance metrics established the reliability of the system classification process:

- Accuracy: Achieved a validation accuracy of 91% (Top-3 accuracy) and 82% (Top2 accuracy).
- The model showed excellent precision together with high recall which led to stable identification of malignant and benign lesions.
- Balanced classification performance was assessed through the F1-Score as well as other measurements.

Comparative Analysis

The proposed system underwent comparison with traditional methods that diagnose skin diseases:

- Standard medical diagnosis processes need specialized medical equipment alongside expert medical personnel involvement.
- Proposed System: Provides a faster, cost-effective, and portable alternative for preliminary skin lesion assessments.

Due to its minimal resource needs MobileNet proved itself as an excellent choice for deploying on constrained mobile devices. The addition of Telegram integration through the platform simplified user operations to increase accessibility in remote locations.

Conclusion

The implemented system proved its capacity to accurately detect skin lesions with real-time analysis features. A solution combining MobileNet CNN and Raspberry Pi deployment besides Telegram integration generated a budget-friendly and easy-to-use system. The proposed system brings advanced accessibility to skin disease detection which leads to early diagnosis to advance patient outcomes.

Key Takeaways

- High classification accuracy with rapid real-time predictions.
- The system operates with minimal computer power because of its simple computational requirements which makes it appropriate for edge devices.
- Instant user notifications via Telegram for improved accessibility. Future Enhancements:
- The system should expand its dataset coverage to representatives of various skin diseases because generalized performance depends on it.
- To achieve even more accurate results developers should enhance the image preprocessing methods.
- An enhancement of the Telegram bot system through addition of voice command systems and multilingual functionalities can be done.

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