" Skin Disease Detection Using MobileNet Deployed on Raspberry Pi with Telegram Bot Integration "

PROJECT WORK - PHASE-2 REPORT

Submitted by

N. SHANMUKHA SAI(21603107)

E.AARTHI(21603116)

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Under the guidance of

Dr.MADONA B SAHAAI

Assistant Professor

Department of Electronics and Communication Engineering,
School of Engineering, VISTAS, Chennai – 600117

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BONAFIDE CERTIFICATE

Certified that this project report titled "**SKIN DISEASE DETECTION USING MOBILENET DEPLOYED ON RASPBERRY PI WITH TELEGRAM BOT INTEGRATION** " is the bonafide work of **N.SHANMUKHA SAI (Reg No: 21603107) and E.AARTHI (Reg No: 21603116)** who carried out the project work under my supervision. Certified further that to the best of my knowledge, the work reported here in does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

SIGNATURE	**SIGNATURE**
Head of Department	**Project Supervisor**
Dr. A. Vijayalakshmi	**Dr. Madona B Sahaai**
Professor	**Assistant Professor**
Department of ECE	**Department of ECE**
VISTAS,Chennai-600117	**VISTAS, Chennai-600117**

For the project work and viva-voce examination held on……………………… VELS Institute of Science Technology & Advanced Studies (VISTAS), Chennai-600117.

`INTERNAL EXAMINER	**EXTERNAL EXAMINER**

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ABSTRACT

Skin diseases require timely diagnosis, but access to dermatological care remains a challenge, especially in remote areas. This project presents a cost-effective and efficient skin disease detection system using MobileNet Neural Network, Raspberry Pi, and Telegram for real-time diagnosis.A key innovation in this system is the application of transfer learning, which enhances classification accuracy while reducing the need for extensive training data and computational resources. MobileNet, a lightweight convolutional neural network (CNN), is deployed on Raspberry Pi, ensuring efficient processing on low-power hardware.Users can capture and upload skin condition images via Telegram, where the model processes the image and returns a classification result with a confidence score. This integration ensures real-time diagnosis, making dermatological assessments more accessible.By leveraging deep learning, embedded systems, and instant communication, this approach improves early detection and healthcare accessibility, addressing the limitations of existing systems.

CHAPTER-1
INTRODUCTION

1.1 BACKGROUND AND CONTEXT :

1.1.1 IMPORTANCE OF EARLY SKIN DISEASE DETECTION

Early detection of skin diseases plays a crucial role in preventing complications, reducing healthcare costs, and improving patient outcomes. Skin conditions range from common infections and allergies to severe diseases like melanoma, which can be life-threatening if not diagnosed in time. Identifying these conditions at an early stage allows for timely medical intervention, minimizing disease progression and improving treatment effectiveness.

1.1.2 PREVENTION OF SEVERE COMPLICATIONS

Early detection and diagnosis of skin diseases play a critical role in preventing the progression of various conditions into more severe and difficult-to-treat stages. Common skin ailments such as eczema, psoriasis, and fungal infections, if left untreated, can escalate over time, leading to persistent discomfort, chronic inflammation, and the potential for serious secondary infections. These complications not only affect the physical well-being of individuals but can also significantly impact their overall quality of life. Furthermore, in more serious cases, such as melanoma and other forms of skin cancer, timely identification is crucial. Early diagnosis considerably enhances the chances of successful treatment, as it allows for the initiation of appropriate medical interventions before the disease advances to a life-threatening stage. As a result, early and accurate detection serves as a cornerstone in both improving patient outcomes and reducing the long-term healthcare burden associated with advanced skin diseases.

1.1.3 COST-EFFECTIVE TREATMENT

When detected early, most skin conditions can be treated with simple medications or lifestyle modifications, reducing the need for expensive treatments, hospital visits, or surgical interventions. Delayed diagnosis, on the other hand, can lead to more advanced conditions requiring costly and complex procedures.

1.1.4 IMPROVED QUALITY OF LIFE

Skin diseases can cause severe physical discomfort, pain, and psychological distress, impacting daily life and mental well-being. Timely identification and treatment help alleviate symptoms early, enhancing the patient's overall quality of life.

1.1.5 REDUCED BURDEN ON HEALTHCARE SYSTEMS

By enabling early detection and intervention, healthcare providers can allocate resources more efficiently, preventing overcrowding in hospitals and clinics. This is especially critical in remote areas with limited access to dermatologists and specialized medical care.

1.1.6 ROLE OF TECHNOLOGY IN EARLY DETECTION

Advancements in deep learning and telemedicine have made it possible to integrate artificial intelligence (AI) into dermatological assessments. Automated detection systems using machine learning models, mobile applications, and embedded devices can assist healthcare professionals in diagnosing skin conditions accurately and efficiently. Such systems are particularly beneficial in rural and underprivileged regions, where specialist care is scarce.

Thus, early skin disease detection is essential for effective treatment, cost savings, and improved healthcare accessibility. Innovations in AI-based detection systems further enhance the efficiency and accessibility of dermatological care, making timely diagnosis possible for a wider population.

1.2 CHALLENGES IN SKIN DISEASE CLASSIFICATION

Accurate classification of skin diseases is a complex task due to various challenges related to data availability, similarity among diseases, environmental factors, and computational limitations. Despite advancements in deep learning and image processing, several obstacles hinder the development of a highly reliable and accessible skin disease classification system.

1.2.1 VARIABILITY IN SKIN CONDITIONS

Skin diseases exhibit diverse appearances based on factors such as skin type, age, ethnicity, and disease progression. The same condition may look different across individuals, making it difficult for machine learning models to generalize effectively.

1.2.2 SIMILARITY BETWEEN DIFFERENT DISEASES

A significant challenge in dermatological diagnosis lies in the high degree of visual similarity that exists between various skin conditions. Many skin diseases present overlapping clinical features, such as similar textures, colors, and lesion shapes, which often leads to misclassification and diagnostic errors. For instance, eczema and psoriasis, though distinct in their underlying causes and treatment protocols, can exhibit comparable visual manifestations, including redness, scaling, and irritation. Likewise, early-stage melanoma can closely mimic the appearance of a benign mole, making it difficult even for experienced dermatologists to accurately differentiate between them without additional diagnostic tools. These similarities underscore the necessity for developing highly specialized diagnostic models equipped with fine-grained classification capabilities. Such models must be trained to recognize subtle distinctions and nuanced patterns within clinical images, enabling more precise identification and reducing the risk of misdiagnosis. Therefore, addressing visual similarities through advanced machine learning approaches is essential for improving diagnostic accuracy and patient outcomes in dermatology.

1.2.3 LIMITED AND IMBALANCED DATASETS

Developing robust deep learning models requires large, high-quality labeled datasets. However, publicly available skin disease datasets are often small, imbalanced, or biased, with some diseases having significantly fewer images than others. This imbalance affects model performance, particularly for rare conditions.

Variations in Image Quality and Lighting Conditions - Images captured using different devices (e.g., smartphones, medical cameras) under varying lighting conditions, resolutions, and angles can introduce inconsistencies. Poor-quality images may lead to incorrect predictions, reducing the model's reliability.

Deploying deep learning models on embedded systems like Raspberry Pi presents computational challenges. Skin disease classification requires high processing power and memory, which may not always be available in low-cost, portable hardware. Optimizing models for efficiency while maintaining accuracy is a critical challenge.

Lack of Standardization in Medical Annotations - Medical professionals may have subjective differences in diagnosis and labeling, leading to inconsistencies in dataset annotations. This affects model training and evaluation, making it difficult to achieve a standardized classification system.

Ethical and Privacy Concerns - Skin disease classification involves handling sensitive medical images, raising concerns about data security, privacy, and ethical use. Ensuring secure data collection, storage, and compliance with medical regulations is essential for widespread adoption.

1.2.4 ADDRESSING THE CHALLENGES

To overcome these challenges, researchers focus on:

- Transfer learning to improve accuracy with limited data.
- Data augmentation techniques to enhance model generalization.
- Edge AI optimizations for real-time processing
- Standardized datasets and annotations for better consistency.
- Secure and privacy-preserving frameworks processing.

Despite these challenges, advancements in deep learning, cloud computing, and embedded AI continue to improve the accuracy and accessibility of skin disease classification systems.

1.3 ROLE OF DEEP LEARNING IN HEALTHCARE

Deep learning has revolutionized healthcare by enabling automated, accurate, and efficient diagnosis, prediction, and treatment planning. With its ability to analyze vast amounts of medical data, deep learning enhances disease detection, medical imaging, drug discovery, and personalized treatment, improving patient outcomes and reducing healthcare costs.

1.3.1 DISEASE DIAGNOSIS AND CLASSIFICATION

Deep learning models, particularly Convolutional Neural Networks (CNNs), are widely used for medical image analysis, helping detect diseases such as cancer, skin conditions, pneumonia, and diabetic retinopathy with high accuracy. These models can analyze X-rays, MRIs, CT scans, and dermatological images, providing automated and reliable diagnoses.

1.3.2 MEDICAL IMAGE PROCESSING AND SEGMENTATION

Advanced deep learning techniques such as U-Net and Fully Convolutional Networks (FCNs) enable precise segmentation of tumors, lesions, and abnormalities in medical scans. This helps radiologists and dermatologists identify and assess diseases at an early stage, improving treatment efficiency.

1.3.3 PREDICTIVE ANALYTICS AND EARLY DISEASE DETECTION

By analyzing electronic health records (EHRs), genetic data, and real-time patient monitoring, deep learning can predict disease risks, progression, and complications. This is particularly useful in detecting chronic conditions such as cardiovascular diseases, diabetes, and neurodegenerative disorders before severe symptoms appear.

1.3.4 DRUG DISCOVERY AND DEVELOPMENT

Deep learning accelerates drug discovery and personalized medicine by analyzing chemical compositions and biological interactions. AI-driven models help identify potential drug candidates, predict side effects, and optimize treatments, significantly reducing the time and cost of pharmaceutical research.

1.3.5 ROBOTICS AND SMART HEALTHCARE SYSTEMS

Deep learning powers AI-driven robotic surgery, prosthetics, and assistive devices that enhance precision in medical procedures. Additionally, chatbots and virtual assistants provide real-time patient support, mental health monitoring, and telemedicine services, improving healthcare accessibility.

1.3.6 REMOTE HEALTHCARE AND TELEMEDICINE

Deep learning, integrated with IoT and mobile applications, enables real-time monitoring of patient vitals, remote diagnostics, and virtual consultations. This is particularly beneficial for rural and underprivileged areas where medical resources are scarce.

Challenges and Future Directions

Despite its advantages, deep learning in healthcare faces challenges are:

- Data privacy and security concerns in handling sensitive records.
- Need for large, high-quality annotated datasets for training models.
- Computational limitations in real-time applications on edge devices.
- Regulatory approvals and ethical considerations for diagnostics.

Continued advancements in AI, cloud computing, and federated learning aim to address these challenges, making deep learning an integral part of next-generation healthcare solutions.

1.4 ROLE OF AI IN ENHANCING SKIN DISEASE DIAGNOSIS ACCURACY

Artificial Intelligence (AI) has significantly improved the accuracy and efficiency of skin disease diagnosis by leveraging deep learning, computer vision, and medical image processing. Traditional dermatological assessments rely on visual examination and biopsy results, which can be time-consuming and prone to human error. AI-driven systems, particularly Convolutional Neural Networks (CNNs) and transfer learning, have revolutionized the field by providing automated, high-precision skin disease classification and early detection.

1.4.1. IMPROVED IMAGE-BASED DIAGNOSIS USING DEEP LEARNING

The integration of deep learning techniques into dermatological diagnostics has revolutionized the way skin diseases are identified and classified. Advanced deep learning models, particularly architectures such as MobileNet, ResNet, and EfficientNet, have demonstrated remarkable effectiveness in analyzing dermatological images. These models are extensively trained on large-scale dermatological datasets containing a diverse range of skin conditions, allowing them to learn intricate patterns, textures, and features associated with different diseases.

Through this rigorous training process, they are capable of accurately recognizing and classifying a wide variety of skin ailments, including melanoma, eczema, psoriasis, and bacterial or fungal infections. In many cases, the diagnostic performance of these models matches or even surpasses that of experienced dermatologists, particularly in terms of speed, consistency, and sensitivity. The ability of deep learning models to provide rapid, reliable, and scalable diagnostic support holds immense potential for improving early detection rates, facilitating timely treatments, and ultimately enhancing patient care outcomes across both clinical and remote settings.

1.4.2. TRANSFER LEARNING FOR ENHANCED ACCURACY

Transfer learning has emerged as a highly effective strategy in the development of artificial intelligence (AI) models for dermatological diagnosis. In this approach, pre-trained neural networks—originally trained on large and diverse datasets such as ImageNet—are fine-tuned using specialized skin disease datasets. By leveraging the rich feature representations already learned during the initial training, these models can adapt more efficiently to the specific task of skin condition classification. This methodology significantly reduces the need for collecting and labeling extensive medical image datasets, which is often a time-consuming and resource-intensive process. Moreover, transfer learning enhances the diagnostic precision of AI systems, enabling them to achieve high levels of accuracy even when working with relatively smaller and domain-specific datasets. As a result, AI-driven diagnostic solutions become more accessible, scalable, and effective, particularly in environments where comprehensive medical data may be scarce. The application of transfer learning thus plays a crucial role in bridging the gap between cutting-edge AI capabilities and real-world clinical needs.

1.4.3. FASTER AND REAL-TIME DIAGNOSIS

Traditional methods of diagnosing skin diseases typically involve scheduling physical consultations with dermatologists, undergoing visual inspections, and in some cases, performing laboratory tests such as biopsies or culture examinations. While effective, these processes are often time-consuming and can lead to considerable delays between initial symptom presentation and the commencement of treatment. Such delays may allow skin conditions to worsen, potentially leading to more complex medical interventions. In contrast, the advent of AI-powered diagnostic systems has introduced a paradigm shift in the speed and accessibility of healthcare delivery. By integrating advanced artificial intelligence models with mobile applications, cloud computing platforms, and Internet of Things (IoT) devices, it is now possible to perform real-time assessment of skin conditions. Users can simply upload clinical images captured via smartphones or specialized imaging devices, and the AI system analyzes these inputs almost instantaneously. The system provides diagnostic results accompanied by confidence scores, helping users and healthcare providers make informed decisions quickly. This capability not only accelerates the diagnostic process but also facilitates early detection and timely intervention, ultimately improving patient outcomes and easing the burden on healthcare infrastructure.

1.4.4. REDUCTION IN HUMAN ERRORS AND SUBJECTIVITY

One of the major advantages of incorporating artificial intelligence into dermatological diagnostics is its ability to deliver consistent and objective assessments. Traditional diagnosis by dermatologists, while highly skilled, is inherently influenced by human factors such as individual experience, judgment, fatigue, and even cognitive bias. As a result, two experts might offer differing opinions when presented with the same skin condition, potentially leading to variations in diagnosis and treatment recommendations. In contrast, AI models, once properly trained, apply the same analytical processes uniformly across all cases. These models base their evaluations purely on learned patterns and data-driven algorithms, minimizing subjectivity and emotional bias. By offering standardized classifications and predictions, AI significantly reduces the risk of misdiagnosis, thereby enhancing the reliability and accuracy of medical decisions. Furthermore, AI systems can consistently maintain high performance levels without the variability seen in human assessments, especially in high-pressure or high-volume clinical settings. This standardization not only improves patient outcomes but also builds greater confidence in automated diagnostic tools among healthcare providers and patients alike.

1.4.5 Enhanced Diagnosis in Remote and Underserved Areas

AI-powered telemedicine solutions integrated with platforms like Telegram bots or mobile apps enable people in rural and remote areas to receive instant skin disease assessments without the need for in-person consultations. This improves healthcare accessibility and promotes early detection, preventing disease progression.

1.4.6. CONTINUOUS LEARNING AND MODEL IMPROVEMENT

AI-driven skin disease detection systems are not static; rather, they are designed to evolve and enhance their performance over time through continuous learning and systematic model updates. Initially trained on large datasets of annotated dermatological images, these models establish a strong foundation for recognizing common skin conditions. However, as the system encounters more diverse clinical images — including rare and atypical presentations — it refines its predictive capabilities. This dynamic learning process ensures that the AI model remains up-to-date with the latest medical knowledge and diagnostic standards.

As healthcare institutions and researchers contribute newly annotated datasets, the model's accuracy and generalization abilities improve substantially. This adaptability is crucial, especially given the constantly evolving nature of medical science and the discovery of new or mutated skin diseases. Through periodic retraining, fine-tuning, and algorithmic enhancements, AI models become more robust and capable of identifying an even wider spectrum of dermatological conditions, including those previously underrepresented in initial training sets. Consequently, continuous learning not only boosts diagnostic precision but also extends the utility of AI systems in real-world clinical environments, ensuring long-term relevance and effectiveness.

1.4.7. INTEGRATION WITH DERMATOLOGY WORKFLOWS

AI does not replace dermatologists but acts as a decision-support tool. It helps prioritize severe cases, assist in triage, and provide second opinions, allowing dermatologists to focus on complex cases requiring human expertise.

1.5 DESCRIPTION OF BASAL CELL CARCINOMA (BCC) AND ACTINIC KERATOSIS AND INTRAEPITHELIAL CARCINOMA:

Fig.1.5.1 Basal Cell Carcinoma (BCC)

Basal Cell Carcinoma (BCC) is recognized as the most prevalent form of skin cancer, originating specifically in the basal cells located within the deepest layer of the epidermis. This condition is primarily attributed to prolonged and unprotected exposure to ultraviolet (UV) radiation, either from sunlight or artificial sources like tanning beds. The continuous UV damage triggers mutations in the skin cells, leading to abnormal, uncontrolled cellular growth.

Clinically, BCC manifests in various forms, including a pearly or waxy bump, a flat and scaly reddish patch, or a persistent sore that fails to heal over time. These lesions are predominantly found on areas frequently exposed to the sun, such as the face, neck, scalp, ears, shoulders, and hands. Although Basal Cell Carcinoma is characterized by its slow growth rate and rare tendency to metastasize to distant organs, neglecting early treatment can result in significant local tissue destruction, leading to disfigurement and functional impairments in severe cases.

Early diagnosis plays a crucial role in improving patient outcomes, and advancements in dermatological screening combined with AI-based image analysis technologies have significantly enhanced early detection capabilities. These technologies assist in identifying suspicious lesions with high accuracy, enabling timely medical intervention. A range of treatment options is available depending on the size, depth, and location of the tumor. These include surgical excision, cryotherapy (freezing the lesion), laser therapy, Mohs micrographic surgery for high-risk areas, and topical chemotherapeutic agents. Personalized treatment planning ensures optimal cosmetic and functional results while minimizing the risk of recurrence.

Fig.1.5.2 Actinic Keratosis

Actinic Keratosis (AK) is a common precancerous skin condition that develops primarily as a result of long-term and cumulative exposure to ultraviolet (UV) radiation from the sun or artificial UV sources. Individuals with fair skin, light-colored eyes, and a history of excessive sun exposure or frequent tanning bed use are at a particularly elevated risk of developing AK. The lesions typically manifest as rough, scaly, crusty, or dry patches that can vary in color from skin-toned to reddish-brown. These lesions most often appear on sun-exposed areas of the body such as the face, scalp, ears, lips, neck, forearms, and the backs of the hands.

Actinic Keratosis serves as an important clinical warning sign because it carries the potential to progress into Squamous Cell Carcinoma (SCC), a more serious form of skin cancer, if left untreated. Although AK lesions may initially be small, asymptomatic, and subtle, they can gradually enlarge, become inflamed, tender to touch, or develop a thicker, wart-like appearance over time. Therefore, early identification and proactive management are crucial in preventing malignant transformation.

For diagnosis, dermatologists often employ a combination of clinical examination, dermoscopy (a specialized skin imaging technique), and, increasingly, AI-assisted image analysis tools that improve diagnostic accuracy and support early intervention. In certain cases, a skin biopsy is performed to confirm the diagnosis and rule out invasive carcinoma.

Treatment modalities for Actinic Keratosis are varied and chosen based on the number, size, and location of the lesions. Common treatment options include cryotherapy (freezing the lesion with liquid nitrogen), topical chemotherapy using agents such as 5-fluorouracil (5-FU) to selectively destroy abnormal cells, photodynamic therapy (PDT) where light-sensitive medication is activated by a light source to eradicate damaged cells, and advanced laser treatments that precisely target the affected tissue.

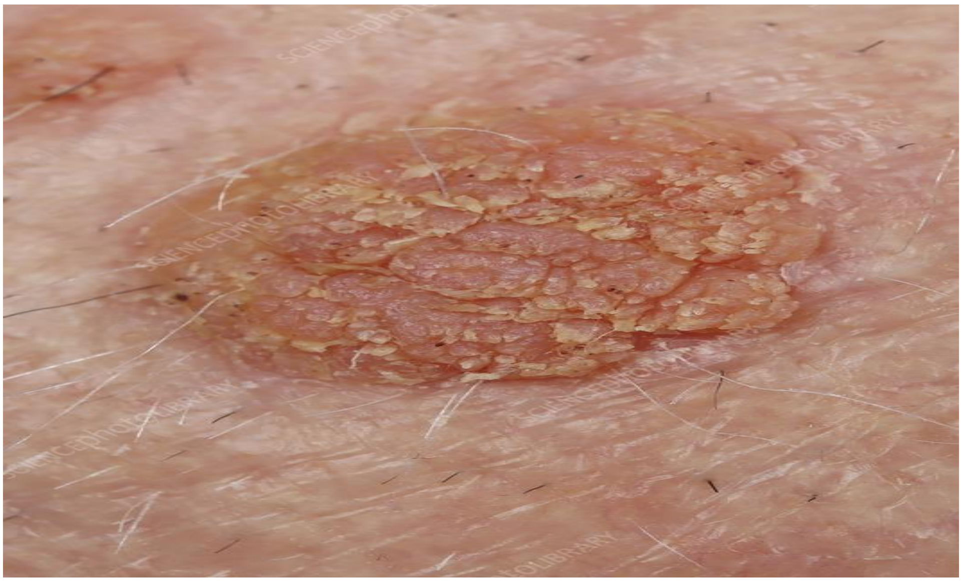


Fig.1.5.3 Intraepithelial Carcinoma

Intraepithelial Carcinoma (IEC), also known as Bowen's Disease, is an early-stage form of Squamous Cell Carcinoma (SCC) in situ, where cancerous cells are confined to the upper layers of the epidermis. It presents as slow-growing, reddish, scaly patches with irregular borders that may resemble eczema or psoriasis. Unlike invasive SCC, IEC remains localized but has the potential to progress into invasive carcinoma if untreated. Common causes include chronic UV exposure, human papillomavirus (HPV) infection, and immunosuppression. Early detection using dermatoscopic imaging and AI-based classification enhances diagnosis accuracy. Treatments such as topical chemotherapy, cryotherapy, curettage, photodynamic therapy, and surgical excision effectively manage the condition. Preventative measures like sun protection, routine skin screenings, and early intervention significantly reduce the risk of progression.

AI-powered skin disease diagnosis is transforming dermatological care by providing fast, accurate, and accessible solutions. By integrating deep learning with mobile technology and cloud-based systems, AI enhances diagnostic accuracy while bridging the gap between specialist healthcare services and underserved populations. Ongoing research and advancements will continue to refine AI models, making them more reliable, inclusive, and widely adopted in clinical practice.
Thus, early skin disease detection is essential for effective treatment, cost savings, and improved healthcare accessibility. Innovations in AI-based detection systems further enhance the efficiency and accessibility of dermatological care, making timely diagnosis possible for a wider population.

CHAPTER -2

LITERATURE SURVEY

2.1 Title: "Global cancer statistics"; Authors: Lindsey A Torre 1, Freddie Bray, Rebecca L Siegel, Jacques Ferlay, Joannie Lortet-Tieulent, Ahmedin Jemal;
Journal Name: CA: A Cancer Journal for Clinicians; Year:2012.

This article provides a status report on the global burden of cancer worldwide using the GLOBOCAN 2018 estimates of cancer incidence and mortality produced by the International Agency for Research on Cancer, with a focus on geographic variability across 20 world regions. There will be an estimated 18.1 million new cancer cases (17.0 million excluding nonmelanoma skin cancer) and 9.6 million cancer deaths (9.5 million excluding nonmelanoma skin cancer) in 2018. In both sexes combined, lung cancer is the most commonly diagnosed cancer (11.6% of the total cases) and the leading cause of cancer death (18.4% of the total cancer deaths), closely followed by female breast cancer (11.6%), prostate cancer (7.1%), and colorectal cancer (6.1%) for incidence and colorectal cancer (9.2%), stomach cancer (8.2%), and liver cancer (8.2%) for mortality. Lung cancer is the most frequent cancer and the leading cause of cancer death among males, followed by prostate and colorectal cancer (for incidence) and liver and stomach cancer (for mortality). Among females, breast cancer is the most commonly diagnosed cancer and the leading cause of cancer death, followed by colorectal and lung cancer (for incidence), and vice versa (for mortality); cervical cancer ranks fourth for both incidence and mortality. The most frequently diagnosed cancer and the leading cause of cancer death, however, substantially vary across countries and within each country depending on the degree of economic development and associated social and life style factors. It is noteworthy that high-quality cancer registry data, the basis for planning and implementing evidence-based cancer control programs, are not available in most low- and middle-income countries. The Global Initiative for Cancer Registry Development is an international partnership that supports better estimation, as well as the collection and use of local data, to prioritize and evaluate national cancer control efforts

2.2 Title: "Melanoma Detection Using Convolutional Neural Networks"; Authors: E. Nasr-Esfahani, S. Samavi, N. Karimi, S. M. R. Soroushmehr, M. H. Jafari, K. Ward, and K. Najarian; Journal Name: IEEE Engineering in Medicine and Biology Society (EMBC); Year: 2016

This study proposed an innovative and robust deep learning-based system designed for the detection of melanoma lesions from clinical (non-dermoscopic) images, a critical advancement in the field of dermatological diagnostics. The system leverages a pre-trained Convolutional Neural Network (CNN), which was implemented on a server equipped with a powerful Graphics Processing Unit (GPU), ensuring high computational efficiency for processing complex image data.

The core methodology of the proposed system involves preprocessing clinical images to minimize common artifacts such as noise and variations in illumination, which are often present in images captured under real-world conditions. By enhancing the quality of the input images, the system ensures that the CNN can more accurately differentiate between melanoma and benign lesions. Preprocessing techniques such as contrast adjustment, noise reduction, and normalization were likely applied to enhance the features relevant for classification.

2.3 Title: "Analysis of CNN Architectures with Transfer Learning for Skin Disease Diagnosis"; Authors: Rifat Sadik, Anup Majumder, Al Amin Biswas, Bulbul Ahammad, and Md. Mahfujur Rahman; Journal Name: Healthcare Analytics; year: 2023

in their study, proposed an efficient solution for skin disease recognition using Convolutional Neural Network (CNN) architectures combined with transfer learning. The study addressed challenges such as low contrast and visual similarity between different skin conditions by employing CNN models like MobileNet and Xception, pre-trained on the ImageNet dataset. Their system aimed to enhance feature discovery and classification accuracy. Additionally, the performance of their approach was compared with other popular architectures like ResNet50, InceptionV3, Inception-ResNet, and DenseNet. Using data collected from two different sources covering five types of skin disorders, they evaluated their models based on accuracy, precision, recall, and F1-score. Experimental results showed that MobileNet achieved 96% accuracy and Xception achieved 97% accuracy with transfer learning and data augmentation. Furthermore, a web-based architecture was developed for real-time skin disease recognition, demonstrating the practical applicability of their approach.

2.4 Title: "Security Analysis Testing for Secure Instant Messaging in Android: A Case Study on Telegram"; Authors: Aditya Candra, Yusuf Kurniawan, and Kyung Hyune Rhee; Journal Name: International Conference on Frontiers of Information Technology (FIT); Year: 2016

proposed a security analysis methodology specifically for secure instant messaging applications on the Android platform, with a focused case study on Telegram. Recognizing the growing popularity and critical need for security in mobile messaging apps, the authors performed a structured threat analysis, identifying potential attack vectors and vulnerabilities that could compromise user data and privacy. Their testing framework involved examining key security aspects such as authentication mechanisms, message confidentiality, data storage, network security, and encryption practices used within the Telegram application.

Through this detailed case study, they highlighted both the strengths and weaknesses in Telegram's security design, providing insights into real-world implementation gaps and how these could be exploited by attackers. The results of the study suggested several improvements for strengthening the overall security posture of instant messaging apps. Their research emphasized the importance of proactive security testing during the development phase to ensure better protection of user information and communications.

2.5 Title: "A Review on Skin Cancer Detection and Classification using Infrared images"; Authors: Akila Victor, Bhuvanjeet Singh

Gandhi, Muhammad Rukunuddin Ghalib, Asha Jerlin M; Journal Name: IJETT; Year:2022

In this study skin cancer is considered one of the most complex forms of cancer. If the skin cancer is not treated early, there is a high possibility that cancer could spread to different parts of the body. Melanoma skin cancer count has been increasing day by day. Early detection plays a very vital role in the treatment of cancer. However, present-day technological developments can detect skin cancer as early as possible. This review focuses on the characteristic features such as texture, shape, color, and structure, the essential paradigm for detecting skin cancer. In medical image processing, skin cancer detection at its initial stage can be done through computer-aided detection, artificial intelligence, swarm technique, etc. In the case of an automatic diagnosis system, there are, most importantly, two major steps, namely skin anomaly detection, and classification. We present a thorough review of skin cancer detection and classification using infrared imaging, artificial neural networks, Gaussian classifiers, etc. This review also delivers obligatory information on numerous techniques and primary steps for the automatic detection and classification of skin cancer.

2.6 Title: "Skin Texture Recognition through Image Processing"; Authors: Sharma, S., & Dubey, A. ; Journal Name: i-manager; Year: 2019

The paper focuses on analyzing the intricate textures of the skin using digital images, which can be crucial in the early detection of skin diseases, including various types of skin cancer. The authors applied image processing algorithms to extract relevant texture features from the skin images, enabling the system to differentiate between normal and abnormal skin textures. This approach has significant implications for dermatology, where accurate texture recognition can assist in identifying underlying skin conditions that are not immediately visible to the naked eye.

The study demonstrated how image processing methods, combined with machine learning algorithms, can be utilized to achieve efficient and reliable skin texture classification. By focusing on texture-based features, the method improves the precision of skin condition diagnoses, reducing the reliance on manual inspection and enhancing the overall accuracy of clinical evaluations. This research highlights the potential of integrating automated image processing systems into clinical practice, offering support to dermatologists in their decision-making process and leading to earlier intervention for patients with skin diseases.

2.7 Title: "Expert System For Diagnosis Of Skin Diseases"; Authors: A.A.L.C. Amarathunga, E.P.W.C. Ellawala, G.N. Abeysekara, C. R. J. Amalraj; Journal Name: Scientific & Technology Research; Year: 2015

In this research they demonstrated how Dermatology is a one of major session of medicine that concerned with the diagnosis and treatment of skin diseases. Skin diseases are the most common form of disease in humans. Recently, many of researchers have advocated and developed the imaging of human vision or in the loop approach to visual object recognition. This research paper presents a development of a skin diseases diagnosis system which allows user to identify diseases of the human skin and to provide advises or medical treatments in a very short time period. For this purpose, user will have to upload an image of skin disease to our system and answer questions based on their skin condition or symptoms. It will be used to detect diseases of the skin and offer a treatment recommendation. This system uses technologies such as image processing and data mining for the diagnosis of the disease of the skin. The image of skin disease is taken and it must be subjected to various preprocessing for noise eliminating and enhancement of the image. This image is immediately segmentation of images using threshold values. Finally data mining techniques are used to identify the skin disease and to suggest medical treatments or advice for users. This expert system exhibits disease identification accuracy of 85% for Eczema, 95% for Impetigo and 85% for Melanoma.

2.8 Title: "Melanoma Segmentation Based on Multi-stage Approach Using Fuzzy and Graph-Cuts Methods"; Authors: Olusoji B.

Akinrinade, Pius A. Owolawi, Chunling Du, Temitope Mapayi; Journal Name: Springer Singapore; Year: 2020

In their 2020 study, Akinrinade et al. proposed an innovative multi-stage approach for melanoma detection, addressing several key challenges in automated skin cancer diagnosis. One of the major hurdles in this field is the quality of input images, which are often affected by noise, low contrast, and difficulties in distinguishing between healthy and diseased skin regions. To tackle these issues, the authors first applied fuzzy transformation techniques to enhance the image, improving its clarity and reducing the negative effects of noise and inconsistent lighting conditions. This step was crucial in preparing the images for accurate analysis, as it made the features of the melanoma lesions more prominent and easier to identify.

Following the enhancement stage, the authors utilized the graph-cuts method for precise segmentation of melanoma lesions. This technique allowed for the effective partitioning of the image into distinct regions, ensuring that melanoma lesions were accurately separated from the surrounding healthy tissue. The experimental results were impressive, with the multi-stage approach achieving a segmentation accuracy of 97.42% and an exceptional specificity rate of 99.07% for background segmentation. These outcomes highlighted the effectiveness of the combined fuzzy and graph-cuts approach in melanoma detection, offering a reliable tool for early diagnosis and improving the overall diagnostic process in clinical settings.

2.9 Title: "The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions"; Authors: Philipp Tschandl, Cliff Rosendahl & Harald Kittler; Journal Name: Scientific Data; Year: 2018

In this research paper they explored Training of neural networks for automated diagnosis of pigmented skin lesions is hampered by the small size and lack of diversity of available datasets of dermatoscopic images. We tackle this problem by releasing the HAM10000 ("Human Against Machine with 10000 training images") dataset. We collected dermatoscopic images from different populations acquired and stored by different modalities. Given this diversity we had to apply different acquisition and cleaning methods and developed semi-automatic workflows utilizing specifically trained neural networks. The final dataset consists of 10015 dermatoscopic images which are released as a training set for academic machine learning purposes and are publicly available through the ISIC archive. This benchmark dataset can be used for machine learning and for comparisons with human experts. Cases include a representative collection of all important diagnostic categories in the realm of pigmented lesions. More than 50% of lesions have been confirmed by pathology, while the ground truth for the rest of the cases was either follow-up, expert consensus, or confirmation by in-vivo confocal microscopy.

2.10 Title: “Skin Lesion Classification Based on Convolutional Neural Network”; Authors: D. B. Mendes and N. C. Silva ; Jounal Name: JASTT; Year: 2022

Skin cancer is one of the most common cancers, and its early detection can have a huge impact on its outcomes. Deep learning, especially convolutional neural networks, perform well in processing massive amounts of data, especially image data in classifying skin cancer. In this paper, convolutional neural networks are mainly used to diagnose and classify 7 types of skin lesions, including melanoma, basal cell carcinoma, melanocytic nevus, actinic keratosis, and intraepithelial carcinoma, benign keratinoid lesions, dermatofibroma, and vascular lesions. First, the characteristics of skin lesion images are analyzed, using image processing technology and sampling technology to preprocess skin lesion images. Then the training parameters of imageNet network are adjusted through the idea of transfer learning on InceptionV3, ResNet50, DenseNet201, and other networks to perform training classification. Furthermore, different convolutional neural network models are built for classification. In order to validate the classification performance of various convolutional neural network models, this paper adopts ISIC 2017 HAM10000 dataset for experiments. The experimental results show that proper preprocessing is necessary when applying CNN for image classification. In classifying the 224*224 skin lesion images.

CHAPTER-3

PROPOSED SYSTEM

3.1 EXISTING SYSTEM:

The current skin disease detection system is based on the MobileNet Convolutional Neural Network (CNN), deployed on a Raspberry Pi and integrated with a Telegram chatbot for real-time image classification. The system allows users to upload skin lesion images via Telegram, which are then processed by the MobileNet model to classify them into different skin disease categories. The Depthwise Separable Convolution used in MobileNet helps reduce computational costs, making it suitable for embedded devices like the Raspberry Pi.

In the existing system, transfer learning is not applied. Instead, the model is trained from scratch using medical image datasets, following a preprocessing pipeline that includes resizing images to 224x224 pixels and converting them to grayscale. The CNN then extracts features and classifies the images into different skin disease types.

The accuracy of the system is measured as follows:

Top-3 validation accuracy: 0.096

Top-2 validation accuracy: 0.89 (89%)

Once the classification is complete, the Telegram bot sends the results back to the user, providing an initial diagnosis. This system aims to assist dermatologists in managing skin disease diagnoses while also offering early detection support for general users.

Despite its effectiveness, the existing system has certain limitations, such as longer training times, higher data requirements, and limited accuracy due to the absence of transfer learning. These challenges highlight the need for improvements in the proposed system, where transfer learning will be incorporated to enhance accuracy, reduce training time, and improve model efficiency.

3.1.1 DRAWBACKS OF THE EXISTING SYSTEM:

While the existing system provides a cost-effective and accessible solution for skin disease detection, it has several limitations that impact its accuracy, efficiency, and scalability. Some of the key drawbacks include:

Lack of Transfer Learning - The model is trained from scratch rather than using transfer learning, which results in longer training times and lower accuracy. Transfer learning could significantly improve performance by leveraging pre-trained models with extensive feature extraction capabilities.

Limited Accuracy - The existing system achieves a top-3 validation accuracy of 0.096 and a top-2 accuracy of 89%, which leaves room for improvement. Misclassifications can occur due to insufficient training data and the lack of transfer learning to refine feature detection.

High Training Costs and Time - Training a deep learning model from scratch requires substantial computational power and time. Since the system relies on Raspberry Pi, a low-power embedded device, training is constrained by hardware limitations, leading to increased processing time.

Small and Imbalanced Dataset - The accuracy of deep learning models depends on the size and diversity of the dataset. The existing system may not generalize well to diverse skin types, lighting conditions, and disease variations, resulting in biased or inaccurate predictions.

Limited Scalability and Generalization - Since the model is trained from scratch on a specific dataset, it may struggle to classify new or rare skin conditions effectively. Without transfer learning, adapting the system to new datasets requires retraining from the beginning, making it less scalable.

Dependence on Image Quality - The system relies on user-uploaded images via Telegram, which can vary in lighting, resolution, and focus. Poor-quality images can lead to incorrect classifications, reducing the system's reliability.

3.2 PROPOSED SYSTEM:

The proposed system enhances the existing skin disease detection model by incorporating transfer learning and replacing MobileNet with a ResNet-based pre-trained model. This approach significantly improves accuracy, efficiency, and scalability while reducing the need for extensive training data and computational resources.

In this system, ResNet (Residual Neural Network), a deep learning model known for its high accuracy and ability to handle vanishing gradient issues, is utilized for skin disease classification. Unlike the existing system, where the model was trained from scratch, the proposed system leverages a pre-trained ResNet model that has already learned essential features from a large dataset. Transfer learning is applied by fine-tuning this model using a skin disease dataset, enabling faster and more accurate classification.

The workflow of the proposed system follows these steps:

Image Acquisition via Telegram: Users upload a skin lesion image using the Telegram chatbot.

Preprocessing: The image is resized and normalized to match the ResNet model's input requirements.

Feature Extraction using Pre-trained ResNet: The pre-trained ResNet model extracts essential features from the image.

Fine-Tuned Classification Layer: A customized classification layer is added and trained on a skin disease dataset to improve performance.

Prediction and Result Display: The model predicts the skin disease and sends the classification result with confidence scores back to the user via Telegram.

3.2.1 ADVANTAGES OF PROPOSED SYSTEM:

Higher Accuracy: By leveraging ResNet and transfer learning, the model achieves better classification accuracy than the existing system.

Reduced Training Time: Since ResNet is already pre-trained, only the final layers need fine-tuning, significantly reducing training time.

Improved Generalization: The model can classify a broader range of skin diseases more effectively, even with a limited dataset.

Efficient Deployment: Despite using a deeper model like ResNet, transfer learning ensures that computational requirements remain manageable for real-world deployment.

3.2.2 BLOCK DIAGRAM OF PROPOSED SYSTEM:

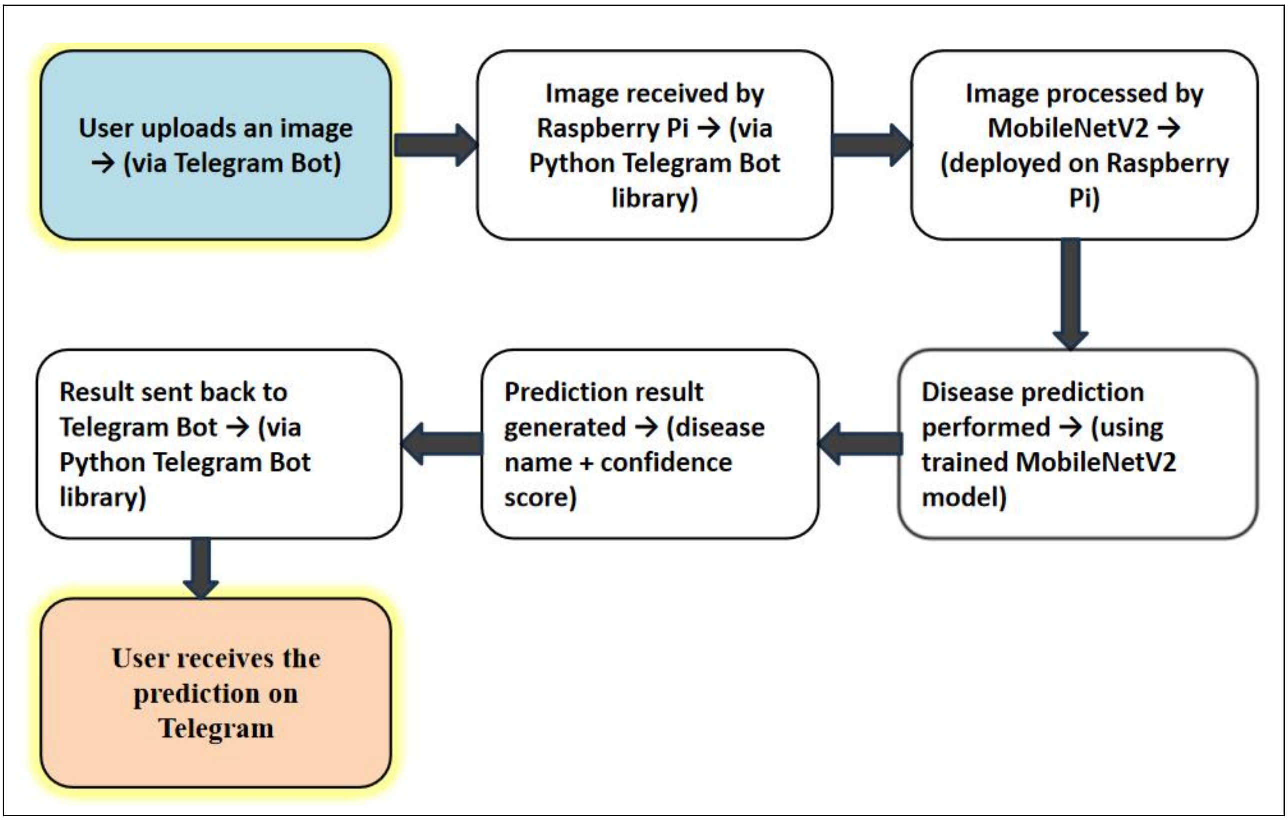


Fig.3.2.1 Block diagram

User Uploads an Image (via Telegram Bot) **-** The user captures or selects an image of the affected skin area and uploads it through a Telegram bot interface.

Image Received by Raspberry Pi (via Python Telegram Bot Library) - The uploaded image is received and processed on a Raspberry Pi, which acts as the edge computing device handling the classification task. The Python Telegram Bot library is used to manage communication between the user and the system.

Image Processed by MobileNetV2 (Deployed on Raspberry Pi) - The MobileNetV2 model, a lightweight and efficient deep learning architecture, processes the image to extract relevant features for classification. This model is deployed directly on the Raspberry Pi, allowing real-time inference.

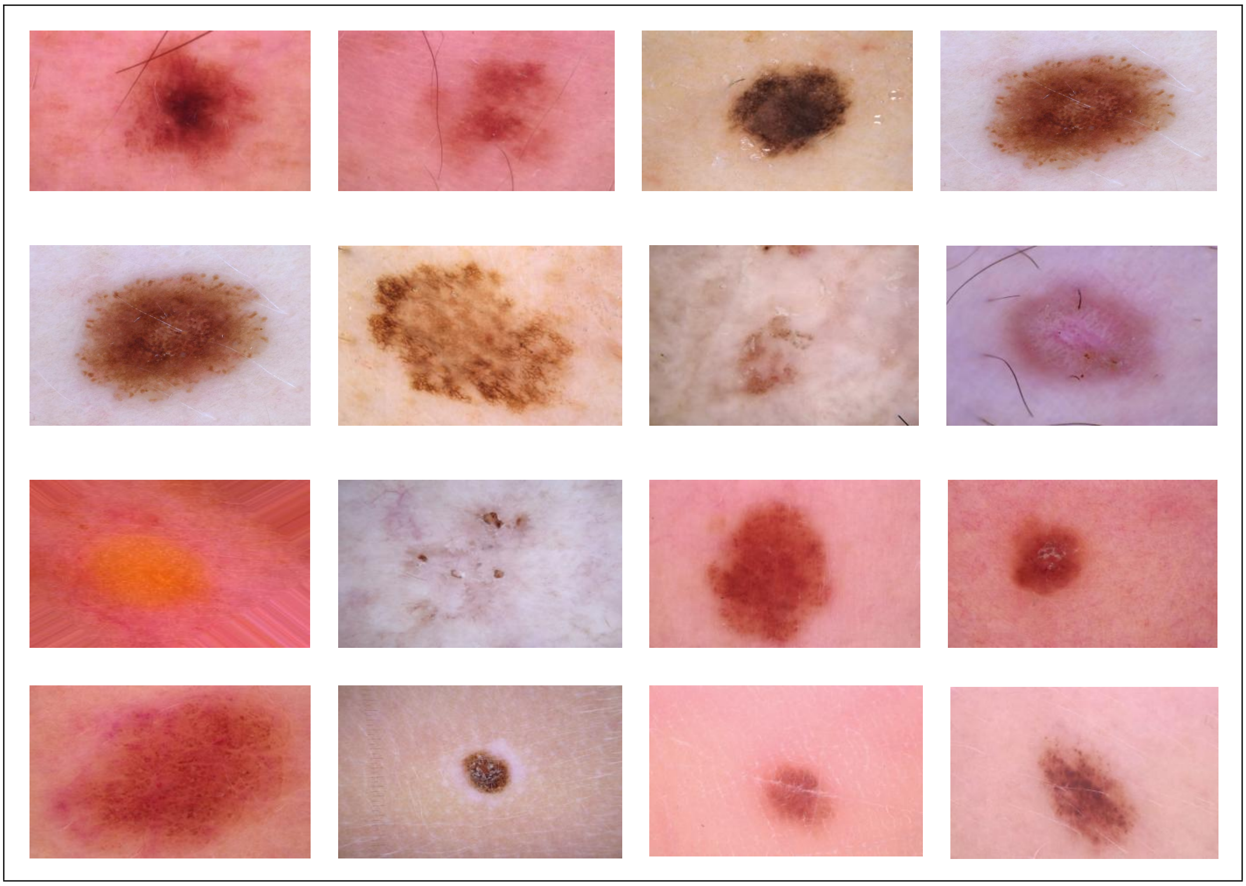
Disease Prediction Performed (Using Trained MobileNetV2 Model) -

The trained MobileNetV2 model analyzes the processed image and classifies the skin disease based on the learned patterns. The model provides an output that includes the predicted disease category.

Prediction Result Generated (Disease Name + Confidence Score) - The system generates a prediction result that consists of The detected skin disease name and a confidence score, indicating how certain the model is about its prediction.

Result Sent Back to Telegram Bot (via Python Telegram Bot Library) - The prediction result is transmitted back to the user through the Telegram bot, making it easily accessible

User Receives the Prediction on Telegram - The final output (disease name and confidence score) is displayed to the user in the Telegram chat, enabling quick and remote diagnosis.



3.2.2 Dataset

3.2.3 IMPLEMENTATION OF MOBILENET NEURAL NETWORK:

Introduction to MobileNet - MobileNet is a lightweight deep learning model designed for mobile and embedded vision applications. It was developed by Google to optimize deep learning models for low-power devices such as mobile phones, Raspberry Pi, and IoT devices. The primary advantage of MobileNet is its ability to achieve high accuracy with minimal computational cost, making it an excellent choice for real-time applications like skin disease detection.

Architecture of MobileNet - The key innovation in MobileNet is the depthwise separable convolution, which drastically reduces the number of parameters and computational complexity compared to traditional CNN architectures.

Depthwise Separable Convolution - MobileNet replaces standard convolutions with depthwise separable convolutions, which break down the convolution process into two steps:

Depthwise Convolution: Applies a single filter per input channel, reducing the computational load.

Pointwise Convolution: Uses 1×1 convolutions to combine the outputs of depthwise convolutions and generate final feature maps.
This approach significantly reduces the number of parameters and improves efficiency without a major loss in accuracy.

Architectural Components - Standard Convolution Layer: Only used in the first layer to capture initial image features.
Depthwise Separable Convolutions: Used throughout the network to minimize computational cost.

Batch Normalization & ReLU Activation: Applied after each convolutional layer for stability and non-linearity.
Global Average Pooling: Reduces the final feature maps to a single vector.

Fully Connected Layer & Softmax Activation: Produces the final classification output.

TABLE 3.2.1 IMPORT REQUIRED LIBRARIES

```
import tensorflow as tf
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.optimizers import Adam
```

3.2.4 ADVANTAGES OF USING MOBILENETV2

- Lightweight → Designed for mobile and embedded devices.
- Faster Inference → Suitable for real-time applications.
- High Accuracy → Despite being lightweight, it delivers results.
- Efficient Parameter Usage → Fewer parameters than CNNs.
- Less Computational Power Required →hardware like Raspberry Pi.

3.2.5 TRANSFER LEARNING FOR SKIN DISEASE DETECTION: INTRODUCTION TO TRANSFER LEARNING:

Transfer Learning is a deep learning technique where a pre-trained model (trained on a large dataset like ImageNet) is reused for a new but similar task, instead of training from scratch. This significantly reduces the training time and improves model accuracy, especially when dealing with small medical datasets like skin disease detection.

For skin disease classification, we can use pre-trained CNN architectures such as MobileNetV2, ResNet50, VGG16, and EfficientNet to extract high-level features and fine-tune the model for dermatology applications.

Why Use Transfer Learning for Skin Disease Detection?

Limited Medical Datasets → Training deep CNNs from scratch requires millions of images, which are often unavailable in medical datasets.

High Accuracy with Pre-trained Models → Models pre-trained on ImageNet (1.2M images, 1000 classes) already understand basic features like edges, colors, and textures, which can be useful for skin disease detection.

Faster Training and Convergence → Since the lower layers have already learned useful features, only the last few layers need training, reducing computational cost.
Improved Generalization → Prevents overfitting when working with small medical datasets.

Benefits of Transfer Learning in Skin Disease Detection:

- Reduces Training Time – Since the model has already learned generic image features, only the final layers need training.
- Improves Accuracy – Pre-trained models generalize well, especially in medical imaging where data availability is limited.
- Requires Less Data – Transfer learning enables effective learning even with small datasets, making it ideal for healthcare applications.
- Avoids Overfitting – Using pre-trained layers prevents the model from memorizing noise in small datasets.

3.2.6 INTEGRATION WITH TELEGRAM FOR REAL-TIME RESULTS:

INTRODUCTION: Integrating deep learning-based skin disease detection with Telegram enables users to receive real-time diagnostic results. This system allows users to upload skin images through a Telegram bot, which processes the images using a MobileNet model deployed on a server or an embedded device (e.g., Raspberry Pi). The bot then returns the predicted skin disease and confidence score.

Why Use Telegram for Real-Time Results?

- Wide Accessibility – Available on mobile, desktop, and web.
- User-Friendly Interface – No need for additional apps; users interact via chat.
- Instant Processing – Model inference is triggered automatically upon image upload.
- Scalability – Can handle multiple user requests asynchronously.

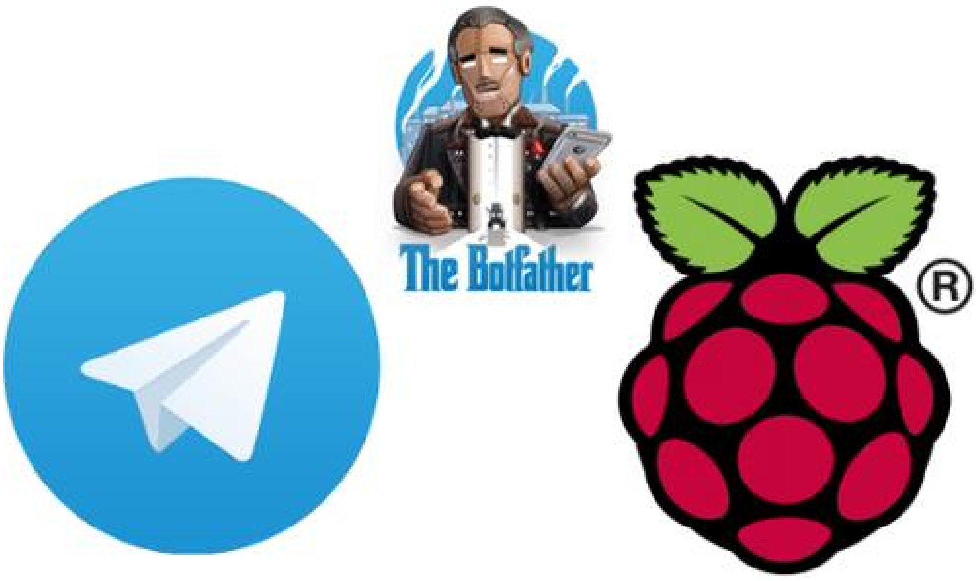


Fig.3.2.3 Bot Father+Raspberry pi

IMPLEMENTATION WORKFLOW: Setting Up the Telegram Bot - Create a bot using the BotFather on Telegram.Obtain the bot token for authentication.
Use the python-telegram-bot library to handle messages and images.

Image Handling and Preprocessing - Convert the received image to a format compatible with MobileNet (224×224 pixels). Normalize pixel values for consistent model input.

Model Inference Using MobileNet - Load the pre-trained MobileNet model (fine-tuned for skin disease detection). Perform inference to obtain the predicted class and probability scores.

CHAPTER-4

SOFTWARE AND HARDWARE

4.1 HARDWARE REQUIREMENTS:

To implement the MobileNet-based Skin Disease Detection System integrated with Telegram, specific hardware components are required to ensure smooth operation. The key hardware components used in this system are:

4.1.1 RASPBERRY PI:

DESCRIPTION: The Raspberry Pi is a small, low-cost, yet powerful single-board computer that serves as the primary processing unit for this system. It is responsible for running the pre-trained MobileNet model, processing the received images for disease classification, and facilitating communication between the Telegram bot and the user. Despite its compact size, the Raspberry Pi is equipped with sufficient processing power to handle various tasks such as image preprocessing, deep learning model execution, and sending back the results to the Telegram bot. This makes it an ideal choice for applications that require low-power, efficient computing solutions, such as medical diagnosis in this case.

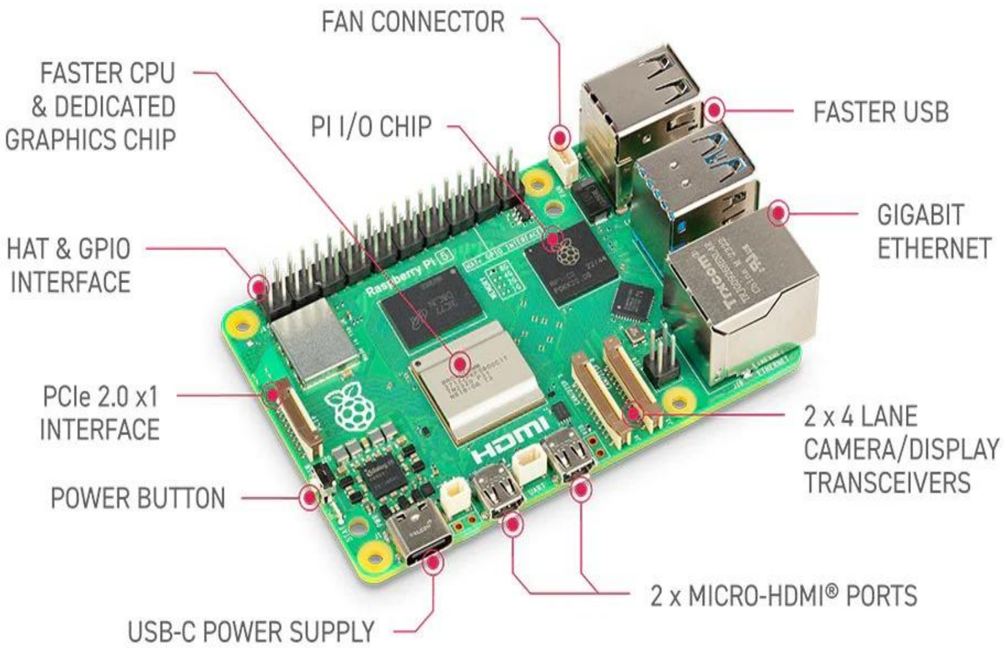


Fig.4.1.1 Raspberry pi parts in detailed

KEY FEATURES:

- Compact and Energy-Efficient – Ideal for edge computing applications.
- Supports Linux-based OS – Runs Raspbian or Ubuntu for model execution.
- Built-in WiFi and Ethernet – Enables internet connectivity for real-time Telegram integration.
- Multiple USB Ports – Allows external peripherals like cameras or additional storage devices.

ROLE IN THE SYSTEM:

- Receives images from the Telegram bot.
- Preprocesses the images (resizing, normalization).
- Runs the MobileNet deep learning model for skin disease classification.
- Sends the prediction results back to the user via Telegram.

4.1.2 POWER ADAPTER FOR RASPBERRY PI

Fig.4.1.2 Power Supply

DESCRIPTION:

The power adapter is essential for providing a stable and continuous power supply to the Raspberry Pi. It ensures that the board operates efficiently without interruptions, especially during high-computation tasks like image processing and deep learning inference.

RECOMMENDED SPECIFICATIONS:

- Output Voltage: 5V

- Current: 3A (recommended for Raspberry Pi 4)
- Connector Type: USB-C (for Raspberry Pi 4) / Micro-USB (for older models)

ROLE IN THE SYSTEM:

- Ensures uninterrupted power supply to the Raspberry Pi.
- Prevents voltage fluctuations that could cause system crashes.

4.1.3 HDMI CABLE

Fig.4.1.3 HDMI for Display

DESCRIPTION:

The HDMI (High-Definition Multimedia Interface) cable is used to connect the Raspberry Pi to an external display, such as a monitor or TV, for system setup, debugging, and monitoring.

KEY FEATURES:

Supports Full HD Output – Enables a clear display of logs and outputs.
Plug-and-Play Connectivity – Easily connects to monitors for GUI-based system setup.

ROLE IN THE SYSTEM:

- Used during the initial setup of the Raspberry Pi OS and software.
- Helps in debugging errors, monitoring logs, and testing model performance.
- Can be disconnected after setup for headless operation.

4.2 SOFTWARE REQUIREMENTS:

Fig.4.2.1 OS

4.2.1. OPERATING SYSTEM: RASPBERRY PI OS (RASPBIAN) / UBUNTU

Description: The Raspberry Pi OS (formerly Raspbian) or Ubuntu serves as the primary operating system for the Raspberry Pi, providing the necessary environment to execute Python scripts, run deep learning models, and manage communication with the Telegram bot. These operating systems are lightweight, efficient, and compatible with a wide range of software, making them ideal for projects like image processing and machine learning applications. Raspberry Pi OS, in particular, is optimized for the hardware of the Raspberry Pi, ensuring smooth operation of tasks such as image recognition and data transmission over networks.

In this project, the Raspberry Pi 4 Model B was used as the central processing unit. The Raspberry Pi 4 Model B is a powerful and versatile single-board computer, equipped with a quad-core ARM Cortex-A72 processor running at 1.5 GHz, making it suitable for running computationally intensive tasks such as deep learning models and image processing algorithms. It comes with options for 2GB, 4GB, or 8GB of RAM, allowing for flexible memory configurations based on the needs of the application. Additionally, it supports dual-display output, USB 3.0, and Gigabit Ethernet, ensuring fast data transmission and a smooth user experience. The increased performance and memory capacity of the Raspberry Pi 4 Model B make it an ideal choice for projects requiring real-time data analysis and efficient processing, such as the skin disease detection system in this project.

FEATURES:

- Lightweight and optimized for Raspberry Pi.
- Linux-based, allowing easy installation of required libraries.
- Supports Python and TensorFlow, enabling deep learning model execution.

ROLE IN THE SYSTEM:

- Runs the Python-based deep learning model.
- Handles communication between hardware and software components.
- Supports system monitoring, debugging, and execution.

4.2.2 PYTHON PROGRAMMING LANGUAGE

FIG.4.2.2 Programming Language

DESCRIPTION:

Python is the primary programming language used for implementing the deep learning model and integrating it with Telegram. It is chosen for its ease of use, extensive library support, and compatibility with TensorFlow and OpenCV.

FEATURES:

- Easy syntax for scripting and automation.
- Supports deep learning frameworks like TensorFlow and Keras.
- Compatible with Raspberry Pi and Telegram APIs.

ROLE IN THE SYSTEM:

- Executes the MobileNet-based deep learning model for skin disease detection.
- Handles image preprocessing and prediction.
- Communicates with Telegram Bot API for real-time interaction.

4.2.3 TENSORFLOW AND KERAS (DEEP LEARNING FRAMEWORKS)

Fig.4.2.3 ML Frameworks

DESCRIPTION:

TensorFlow and Keras are open-source deep learning frameworks that allow us to implement and run the pre-trained MobileNet model on Raspberry Pi. They help in efficient deep learning inference with minimal computational resources.

FEATURES:

- Pre-trained Model Support: Enables Transfer Learning with MobileNet.
- Optimized for Edge Devices: Allows efficient execution on Raspberry Pi.
- Supports Image Processing and Classification.

ROLE IN THE SYSTEM:

- Loads and runs the MobileNet deep learning model for disease classification.
- Performs image transformation and feature extraction.
- Outputs disease prediction with a confidence score.

4.2.4. OPENCV (COMPUTER VISION LIBRARY):

Fig.4.2.4 OpenCV Library

DESCRIPTION:

OpenCV is an open-source computer vision library used for image processing tasks such as resizing, normalization, and format conversion before feeding images into the MobileNet model.

FEATURES:

- Efficient Image Preprocessing.
- Compatible with Raspberry Pi and TensorFlow.
- Optimized for Real-Time Processing.

ROLE IN THE SYSTEM:

- Prepares images (resizing, normalization) before model inference.
- Converts image formats for compatibility with MobileNet.
- Helps in debugging by displaying images if needed.

4.2.5. TELEGRAM BOT API (FOR REAL-TIME INTERACTION)

Description:

The Telegram Bot API serves as the communication bridge between the user and the system. It allows for seamless integration of the skin disease detection system with Telegram, enabling users to interact with the system in real time. Through the Telegram bot, users can easily upload images of their skin, and the bot will promptly send the images to the Raspberry Pi, where the pre-trained MobileNet model processes them for disease classification.

The Telegram Bot API facilitates user-friendly interactions by providing a conversational interface. Once the images are processed and analyzed, the bot sends back the predicted disease along with the confidence score to the user. This real-time interaction allows for a fast and efficient diagnosis, making it a convenient tool for users to receive immediate feedback. The system's ability to respond to users quickly helps overcome traditional diagnostic delays, offering a more accessible and timely solution for skin disease detection. By leveraging the Telegram Bot API, the system can cater to a wide range of users across various devices, ensuring broad accessibility and ease of use.

FEATURES:

Provides Secure and Fast Communication with Raspberry Pi.
Allows Image Uploads and Text-Based Interaction.
Enables Real-Time Result Retrieval.

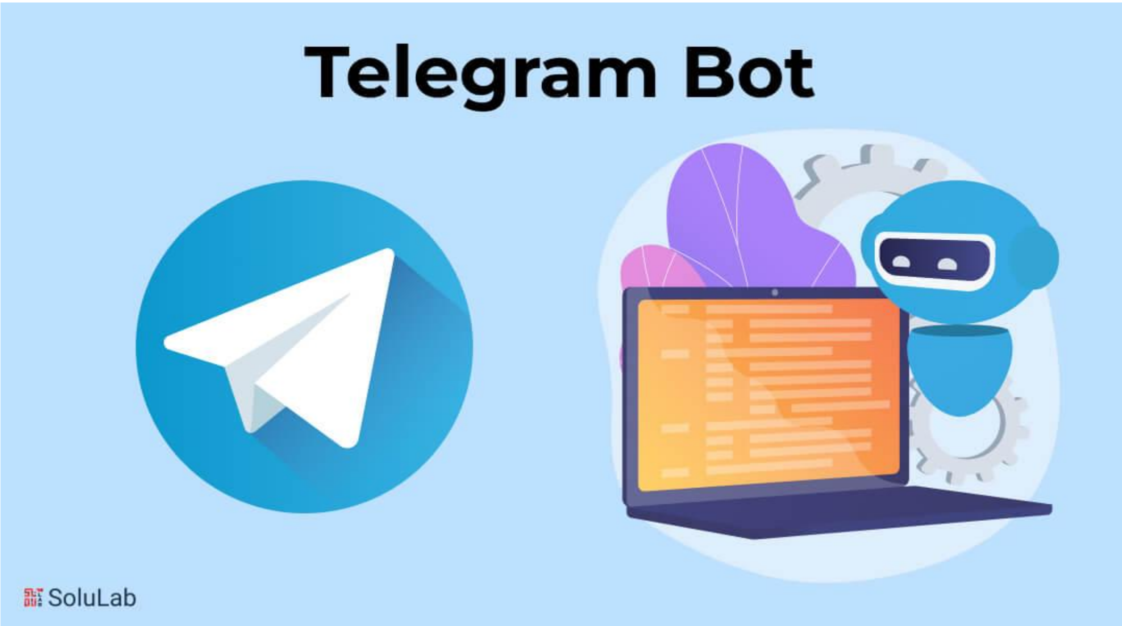


Fig.4.2.5 Telegram Bot

To establish communication between the Raspberry Pi and the Telegram bot, we use the Telegram Bot API. The API token, which is provided by

Telegram when a bot is created via the BotFather, is securely stored and used within the system to facilitate interactions between the user and the bot. The token is kept confidential and is used exclusively for authenticating the bot to send and receive messages from users.

ROLE IN THE SYSTEM:

Accepts image uploads from users.

Sends images to the Raspberry Pi for processing.

Receives and displays predictions (disease name + confidence score).

TABLE 4.2.1 PYTHON LIBRARIES

Library	Purpose
numpy	Handles numerical computations
pillow	Processes, manipulates images
requests	Sends HTTP requests to Telegram API
telebot	telebot
time	Handles time-based operations

4.3 DATASET INFORMATION:

The **HAM10000 dataset** (Human Against Machine with 10,000 Training Images) is one of the most widely used datasets for skin disease classification in deep learning and computer vision research. It contains a diverse collection of dermoscopic images of pigmented skin lesions, making it ideal for training and evaluating machine learning models, particularly in the domain of melanoma detection and general dermatology applications.

Description:

The dataset consists of 10,015 high-quality dermoscopic images. It covers seven different skin lesion categories, ensuring balanced representation of common and rare skin conditions. The images are collected from different sources, including populations from different continents, making the dataset more diverse and robust for real-world applications. It was published by ViDIR Group, Department of Dermatology, Medical University of Vienna, and is widely used for AI-based dermatology studies.

4.3.1 DATASET COLLECTION & ANNOTATION:

Sources:

The images were collected from different hospitals and clinics across Austria and other regions. Data is sourced from diverse populations, ensuring variation in skin tones, lesion types, and age groups. The images are acquired using standardized dermoscopy techniques, ensuring consistency in quality.

Annotation Process:

All images in HAM10000 are expert-labeled and verified by dermatologists. The dataset includes metadata and diagnostic information, allowing deep learning models to be trained with additional clinical context.

4.3.2 APPLICATIONS OF HAM10000 IN DEEP LEARNING

The dataset is extensively used in medical AI research and real-world applications, including: Skin Cancer Detection Models: Training CNN-based models like MobileNet, ResNet, and EfficientNet.

Transfer Learning Applications: Using pre-trained models for rapid adaptation to skin disease classification.

Medical AI Assistance: Assisting dermatologists in diagnosing skin diseases with AI-based tools.

Edge AI Deployment: Optimizing models for real-time inference on Raspberry Pi and mobile devices.

4.4 IMAGE PREPROCESSING TECHNIQUES:

Introduction

Image preprocessing is a crucial step in deep learning and computer vision tasks, especially in medical image analysis. For skin disease detection using MobileNet, preprocessing ensures that input images are standardized, noise-free, and optimized for efficient feature extraction. These techniques enhance the model's performance by improving accuracy and reducing computational complexity.

Importance of Image Preprocessing in Skin Disease Detection: Removes unwanted noise from images, ensuring clearer features. Standardizes image size and format, making it compatible with deep learning models.

Enhances contrast and texture details, helping the model differentiate between similar conditions. Reduces overfitting by increasing dataset diversity through augmentation.

4.4.1 COMMON IMAGE PREPROCESSING TECHNIQUES

4.4.1 a) IMAGE RESIZING

Why? Different images in the dataset may have varying dimensions. Deep learning models like MobileNet require a fixed input size.

How? Images are resized to 224×224 pixels (the default input size for MobileNet).

Effect: Ensures consistency and reduces computational load while maintaining important details.

4.4.1 b) IMAGE NORMALIZATION

Why? Pixel intensity values range from 0 to 255. Normalization helps standardize these values.

How? Convert pixel values to a range of 0 to 1 (by dividing by 255).

Alternative: Use Z-score normalization to standardize mean and variance.

Effect: Prevents large variations in pixel intensity, improving model stability.

4.4.1 c) CONTRAST ENHANCEMENT

Why? Skin lesions may appear faint or unclear due to lighting variations.

How? Histogram Equalization: Distributes pixel intensities evenly across the image.

Adaptive Contrast Stretching: Increases the contrast in darker regions without affecting brighter areas.

Effect: Improves visibility of lesion boundaries, aiding feature extraction.

4.4.1 d) NOISE REDUCTION (DENOISING)

Why? Images may contain artifacts like hair, dust, or uneven lighting.

How? Gaussian Blurring: Reduces minor noise while preserving edges.

Median Filtering: Removes random noise (useful for dermoscopic images).

Effect: Provides cleaner input, preventing false feature detections.

4.4.1 e) IMAGE AUGMENTATION

Why? The dataset may have an imbalance (e.g., fewer melanoma images). Augmentation artificially increases dataset size.

How? Rotation & Flipping: Ensures robustness against different orientations.

Zooming & Cropping: Simulates variations in image capture distances.

Brightness & Contrast Adjustments: Mimics different lighting conditions.

Effect: Enhances model generalization and prevents overfitting.

4.4.1 f) GRAYSCALE CONVERSION

Why? In some cases, color information may not be crucial for classification.

How? Convert RGB images to grayscale by averaging pixel intensity values.

Effect: Reduces computational complexity while preserving essential details.

4.4.1 g) EDGE DETECTION (FEATURE ENHANCEMENT)

Why? Helps highlight lesion boundaries and structural patterns.

How? Canny Edge Detection: Extracts sharp edges.

Sobel Filtering: Enhances directional edges.

Effect: Improves model's ability to recognize lesion boundaries.

4.5 CONFIDENCE SCORE CALCULATION:

How is the Confidence Score Calculated?

Deep learning models like MobileNet use a Softmax activation function in the final layer to assign a probability to each class. The confidence score is the highest probability value among all predicted classes.

4.5.1 SIMPLE EXPLANATION OF THE FORMULA:

The model looks at an image and gives a raw score (logit) for each possible disease.

These scores are converted into probabilities so that they add up to 100%.

The disease with the highest probability is selected as the final prediction.

CHAPTER-5

RESULTS AND DISCUSSION

5.1 BOT EXECUTION ON RASPBERRY PI

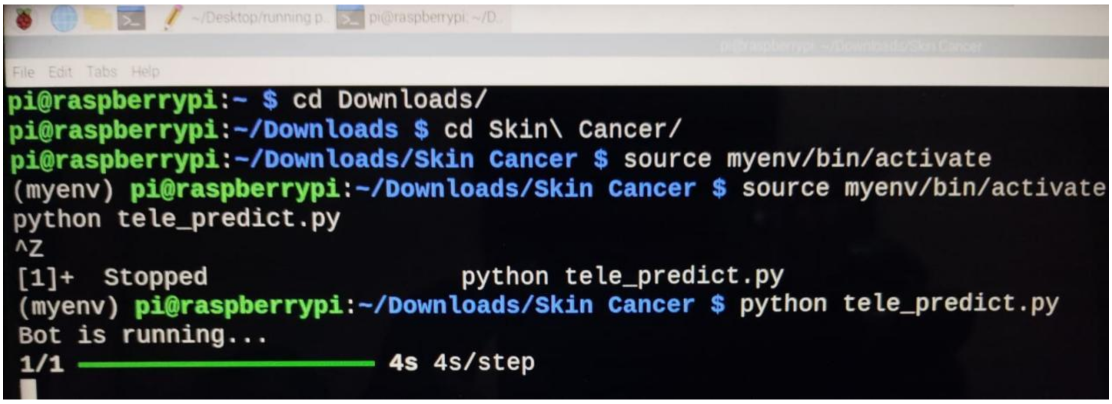


Fig.5.1.1 Bot running

- The bot script tele_predict.py was executed in a virtual environment (myenv) on Raspberry Pi.
- The bot successfully started, displaying "Bot is running...".
- The execution process is visible in the terminal, confirming the bot is active.

5.2 TRAINING AND VALIDATION RESULTS:

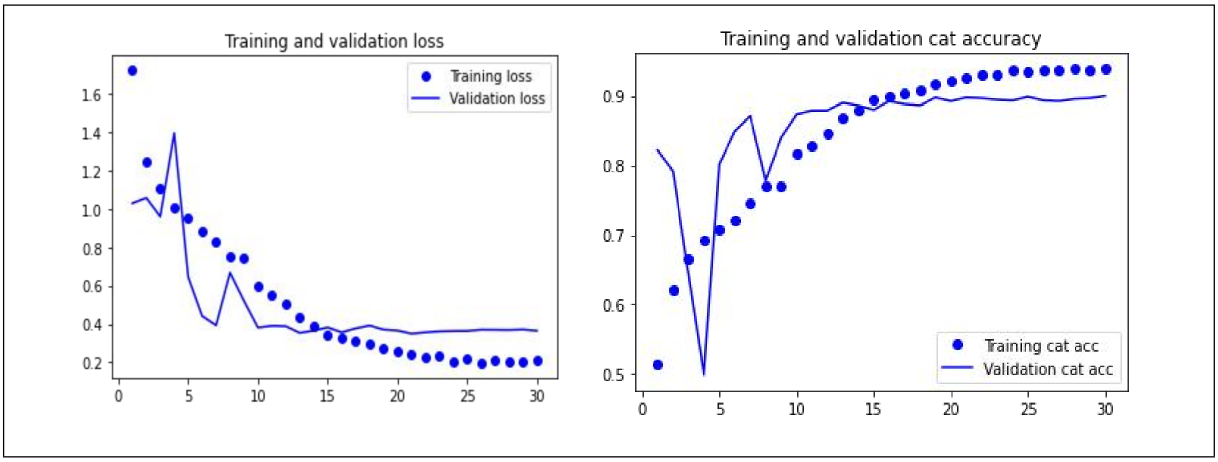


Fig.5.2.1 Training and Validation loss and accuracy

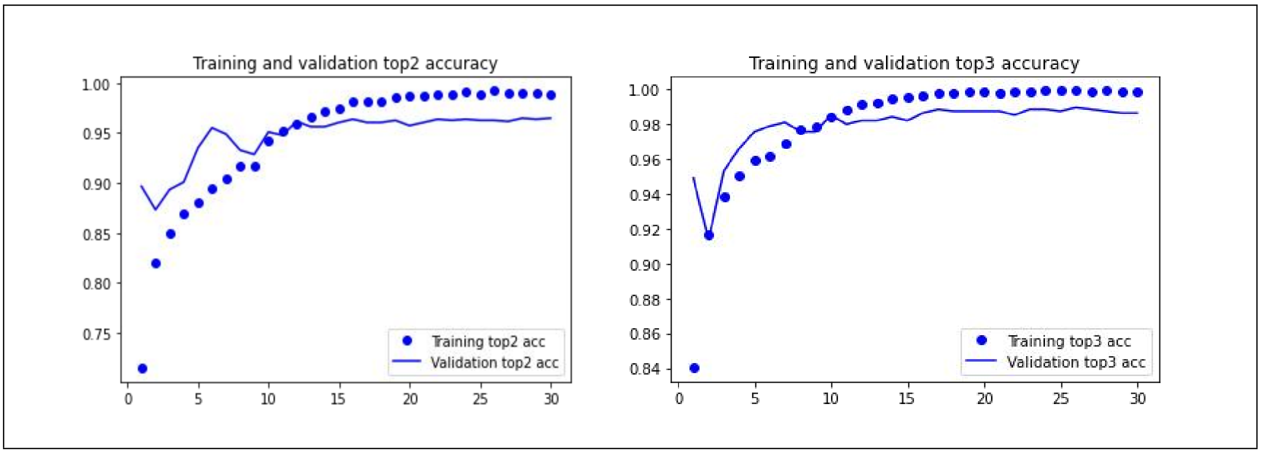


Fig.5.2.2 Training and validation top2 and top3 Accuracy

Table 5.2.1 TRAINING TOP2 WITH TRAINING TOP3 ACCURACY RATES AND TRAINING LOSS OVER THREE DIFFERENT 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

5.3 FINAL OUTPUT AT THE TELEGRAM CHATBOT INTERFACE:

The image provided was analyzed by the skin disease detection system, which utilizes a deep learning model deployed on a Raspberry Pi. The user uploaded the image via a Telegram chatbot, and the system processed it to predict the skin condition. The model classified the lesion as **Actinic Keratoses and Intraepithelial Carcinoma (akiec)** with a confidence score of **90%**. This result was sent back to the user through the Telegram bot, demonstrating the system's ability to provide quick and accurate skin disease predictions.

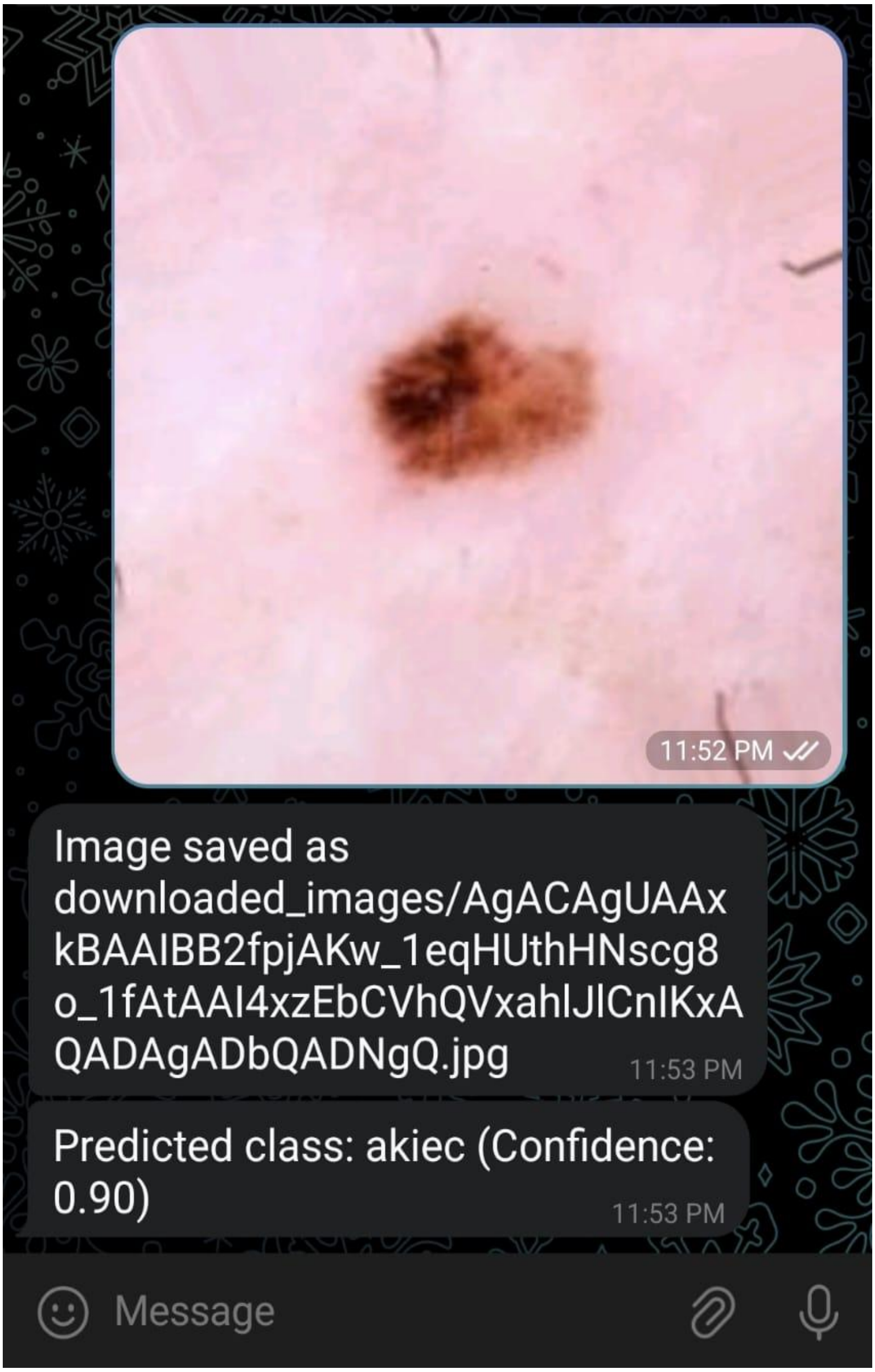


Fig.5.3.1 Output Predicted displayed in telegram

5.4 APPLICATIONS OF SKIN DISEASE DETECTION SYSTEM

The MobileNet-based Skin Disease Detection System has a wide range of applications in healthcare, telemedicine, and AI-driven diagnostics. By integrating deep learning, edge computing, and real-time communication via Telegram, this system provides an efficient and accessible solution for skin disease detection.

5.4 a) TELEMEDICINE AND REMOTE HEALTHCARE

Enables patients in remote areas to receive preliminary skin disease diagnoses without visiting a hospital.

Helps connect patients with dermatologists for further consultation based on AI-generated reports. Reduces hospital visits and waiting times for minor skin conditions.

Fig.5.4.1 Telemedicine

5.4 b) EARLY SKIN CANCER DETECTION

Aids in detecting melanoma, basal cell carcinoma (BCC), and actinic keratosis (AK) at an early stage.

Provides a confidence score, helping users decide whether to seek medical attention. Increases the chances of early treatment, improving survival rates.

5.4 c) AI-ASSISTED DERMATOLOGY

Acts as a decision-support tool for dermatologists by pre-analyzing images.

Helps in triaging patients by prioritizing severe cases.

Assists junior doctors and medical students in learning about skin disease classification.

5.4 d) MOBILE AND EMBEDDED HEALTHCARE SOLUTIONS

Can be deployed on Raspberry Pi or mobile apps, making skin disease detection portable.
Suitable for health kiosks in rural clinics or pharmacies where specialized dermatologists are unavailable.
Helps in offline diagnosis, reducing dependency on cloud computing.

5.4 e) PUBLIC HEALTH SCREENING PROGRAMS

Useful in mass skin disease screening camps to identify high-risk patients.
Can be deployed in schools, workplaces, and elderly care homes for routine skin check-ups.
Helps government and NGOs in preventive healthcare initiatives.

5.4 f) INTEGRATION WITH SMART WEARABLES (FUTURE SCOPE)

Can be integrated with smartphones, smart mirrors, or wearable skin scanners.
Enables real-time skin health monitoring using AI-based alerts.
Potential for use in cosmetic dermatology for tracking skin conditions over time.

5.4 g) RESEARCH AND MEDICAL AI DEVELOPMENT

Helps researchers improve AI-driven skin disease classification models.
Can be extended to other medical image analysis tasks such as wound detection and burn analysis

Fig.5.4.2 AI Research

CHAPTER-6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION: The MobileNet-based Skin Disease Detection System offers a cost-effective, accessible, and real-time solution for early skin disease diagnosis. By leveraging transfer learning, the system enhances accuracy while minimizing computational costs, making it suitable for low-power devices like Raspberry Pi. The integration with Telegram ensures instant diagnostic results, improving healthcare accessibility, especially in remote areas. The use of confidence scores adds transparency to predictions, enabling users to assess reliability before seeking professional consultation. This approach bridges the gap between deep learning and practical healthcare applications, contributing to early detection, reduced medical costs, and improved patient outcomes.

6.2 FUTURE WORK: focusing on enhancing model accuracy with larger, more diverse datasets and exploring more advanced architectures like ResNet or EfficientNet. Expanding the system to detect more skin diseases and developing a mobile app for direct skin scanning can further improve usability. Integration with wearable devices for continuous skin health monitoring and deploying the model on cloud platforms can enhance scalability. Additionally, ensuring data privacy, regulatory compliance, and clinical validation will be critical for real-world adoption. By incorporating these improvements, the system can become a powerful tool in AI-driven dermatology and telemedicine, offering faster, more reliable, and accessible healthcare solutions globally.

CHAPTER-7
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ANNEXURE 1

CODING

Main.py File**:**

```
import tensorflow
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.metrics import categorical_crossentropy
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Model
from tensorflow.keras.callbacks import ReduceLROnPlateau,
ModelCheckpoint
from tensorflow.keras.metrics import categorical_accuracy,
top_k_categorical_accuracy

def top_3_accuracy(y_true, y_pred):
    return top_k_categorical_accuracy(y_true, y_pred, k=3)

def top_2_accuracy(y_true, y_pred):
    return top_k_categorical_accuracy(y_true, y_pred, k=2)


# SETTING UP THE GENERATORS

# IMAGE-GENERATORS ACCEPTS THE ORIGINAL DATA,RANDOMLY TRANSFORMING IT AND RETURN ONLY THE NEW TRANSFORMED DATA. [AUGMENTATION]

train_path              = 'train'
valid_path              = 'val'
test_path               = 'test'


# DIMENSION OF IMAGE
image_size = 224

# THE IMAGE GENERATOR [KERAS]
```

```
datagen = ImageDataGenerator(
    rotation_range          = 180,
    width_shift_range       = 0.1,
    height_shift_range      = 0.1,
    zoom_range              = 0.1,
    horizontal_flip         = True,
    vertical_flip           = True,
    fill_mode               = 'nearest',
    preprocessing_function                                          =
tensorflow.keras.applications.mobilenet.preprocess_input
    )

train_batches = datagen.flow_from_directory(train_path,
                                target_size=(image_size,image_size),
                                batch_size=80)

valid_batches = datagen.flow_from_directory(valid_path,
                                target_size=(image_size,image_size),
                                batch_size=10)

test_batches = datagen.flow_from_directory(test_path,
                                target_size=(image_size,image_size),
                                batch_size=10,
                                shuffle=False)

#################################################################
##############################

# MOBILENET ARCHITECTURE
# MOBILENET IS A CNN ARCHITECTURE FOR IMAGE
CLASSIFICATION . IT IS FAST AND CUSTOMIZABLE .
# USES DEPTH WISE SEPERABLE CONVOLUTION

mobile = tensorflow.keras.applications.mobilenet.MobileNet()

# MODIFY THE MOBILENET
```

```
#--EXCLUDE LAST 6 LAYERS
x = mobile.layers[-6].output
#--CREATE A DENSE LAYER FOR PREDICTION OF 4 CLASSES
x = Dropout(0.25)(x)
predictions = Dense(4, activation='softmax')(x)

model = Model(inputs=mobile.input, outputs=predictions)

#--LAST 23 LAYERS WILL BE TRAINED AND FREEZING THE WEIGHTS OF REST
for layer in model.layers[:-23]:
   layer.trainable = False

model.compile(Adam(lr=0.01), loss='categorical_crossentropy',
              metrics=[categorical_accuracy, top_2_accuracy, top_3_accuracy])

# CLASS SENSITIVITY , HERE PSORIASIS CLASS IS THE MOST SENSITIVE

class_weights={
   0: 3.0,   # PSORIASIS
   1: 1.5,   # MEASLES
   2: 2.0,   # MELANOMA
   3: 2.4,   # RINGWORM
}

filepath = "model.h5"

##################################################################################################

checkpoint = ModelCheckpoint(filepath, monitor='val_top_3_accuracy', verbose=1,
              save_best_only=True, mode='max')
```

```
reduce_lr = ReduceLROnPlateau(monitor='val_top_3_accuracy', factor=0.5, patience=2,
                              verbose=1, mode='max', min_lr=0.00001)


callbacks_list = [checkpoint, reduce_lr]

history = model.fit_generator(train_batches,
                              class_weight=class_weights,
                              validation_data=valid_batches,
                              epochs=30, verbose=1,
                              callbacks=callbacks_list)


###################################################################################################

#---- TESTING THE MODEL ---- #

# model.load_weights('model.h5')

# val_loss, val_cat_acc, val_top_2_acc, val_top_3_acc = model.evaluate_generator(test_batches)

# print('val_loss:', val_loss)
# print('val_cat_acc:', val_cat_acc)
# print('val_top_2_acc:', val_top_2_acc)
# print('val_top_3_acc:', val_top_3_acc)

# predictions = model.predict_generator(test_batches, verbose=1)
```

Predictor.py file:

```
##########################################################
# To get rid of warnings
import warnings
warnings.filterwarnings('ignore', category=FutureWarning)
import os
```

```
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'  # Suppress TensorFlow
logs
import tensorflow as tf
tf.get_logger().setLevel('ERROR')  # Suppress TensorFlow warnings
#######################################################

import sys
import getopt
import numpy as np
from tensorflow.keras.models import Model
from tensorflow.keras.metrics import categorical_accuracy,
top_k_categorical_accuracy
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing import image
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization
from tensorflow.keras.preprocessing.image import ImageDataGenerator

#######################################################

# Top-k accuracy metrics
def top_3_accuracy(y_true, y_pred):
    return top_k_categorical_accuracy(y_true, y_pred, k=3)

def top_2_accuracy(y_true, y_pred):
    return top_k_categorical_accuracy(y_true, y_pred, k=2)

#######################################################

# Load MobileNetV2 and modify for 7 classes
mobile = tf.keras.applications.MobileNetV2(weights='imagenet',
include_top=False, input_shape=(224, 224, 3))

x = mobile.output  # Use the output of the base MobileNetV2 model
x = tf.keras.layers.GlobalAveragePooling2D()(x)  # Pooling layer
x = Dropout(0.25)(x)  # Add a Dropout layer
x = BatchNormalization()(x)  # Add Batch Normalization layer
predictions = Dense(7, activation='softmax')(x)  # Updated for 7 classes
```

```
model = Model(inputs=mobile.input, outputs=predictions)

# Unfreeze the last few layers for fine-tuning
for layer in model.layers[-23:]:
    layer.trainable = True

# Compile the model with a smaller learning rate
model.compile(
    optimizer=Adam(learning_rate=0.0001),  # Use a smaller learning rate
for fine-tuning
    loss='categorical_crossentropy',
    metrics=[categorical_accuracy, top_2_accuracy, top_3_accuracy]
)

# Load the weights excluding the final layer mismatch
model.load_weights('model.h5', by_name=True, skip_mismatch=True)

#####################################################

# Update class labels
class_labels = ["akiec", "bcc"]

######################################################

# Handle command-line arguments
inputfile = 'ISIC_0031298.jpg'
opts, args = getopt.getopt(sys.argv[1:], "hi:o:", ["ifile="])
for opt, arg in opts:
    if opt == '-h':
        sys.exit()
    elif opt in ("-i", "--ifile"):
        inputfile = arg

######################################################

# Function to load and predict images
def loadImages(path):
```

```
    img = image.load_img(path, target_size=(224, 224))  # Resize image to match MobileNetV2 input
    img_data = image.img_to_array(img)  # Convert image to array
    img_data = np.expand_dims(img_data, axis=0)  # Add batch dimension
    img_data = tf.keras.applications.mobilenet_v2.preprocess_input(img_data)  # Preprocess for MobileNetV2
    features = np.array(model.predict(img_data))  # Predict the class
    y_classes = features.argmax(axis=-1)  # Get the index of the highest probability
    return y_classes

######################################################

# Predict and display the class label
x = loadImages(inputfile)
print(class_labels[x[0]])
```

Tele_Predictor.py:

```
import os
import warnings
import numpy as np
import tensorflow as tf
from telegram import Update
from telegram.ext import Application, MessageHandler, filters, ContextTypes
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization
from tensorflow.keras.preprocessing import image
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.metrics import categorical_accuracy, top_k_categorical_accuracy

# Suppress warnings
warnings.filterwarnings('ignore', category=FutureWarning)
```

```
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'  # Suppress TensorFlow logs
tf.get_logger().setLevel('ERROR')  # Suppress TensorFlow warnings

# Replace with your bot token
BOT_TOKEN = "7603548716:AAFsHoZX50nYjWjPFkOxbDiED5bjWyoPlOk"

# Folder to save downloaded images
DOWNLOAD_FOLDER = "downloaded_images"

# Create the download folder if it doesn't exist
if not os.path.exists(DOWNLOAD_FOLDER):
    os.makedirs(DOWNLOAD_FOLDER)

# Class labels for prediction
class_labels = ["bcc", "akiec"]

# Load MobileNetV2 and modify for 2 classes
mobile = tf.keras.applications.MobileNetV2(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
x = mobile.output
x = tf.keras.layers.GlobalAveragePooling2D()(x)
x = Dropout(0.25)(x)
x = BatchNormalization()(x)
predictions = Dense(len(class_labels), activation='softmax')(x)  # Updated for 2 classes
model = Model(inputs=mobile.input, outputs=predictions)

# Unfreeze the last few layers for fine-tuning
for layer in model.layers[-23:]:
    layer.trainable = True

# Compile the model
model.compile(
    optimizer=Adam(learning_rate=0.0001),
    loss='categorical_crossentropy',
```

```
    metrics=[categorical_accuracy, top_k_categorical_accuracy]
)

# Load the weights
model.load_weights('best_model.h5', by_name=True,
skip_mismatch=True)

# Function to predict the class of an image
def predict_image_class(image_path):
    img = image.load_img(image_path, target_size=(224, 224))  # Resize
image
    img_data = image.img_to_array(img)  # Convert to array
    img_data = np.expand_dims(img_data, axis=0)  # Add batch
dimension
    img_data =
tf.keras.applications.mobilenet_v2.preprocess_input(img_data)  #
Preprocess for MobileNetV2
    predictions = model.predict(img_data)  # Predict the class probabilities
    predicted_class_index = np.argmax(predictions, axis=-1)  # Get the
index of the highest probability
    confidence = np.max(predictions)  # Get the confidence of the
prediction
    return class_labels[predicted_class_index[0]], confidence

# Handler for receiving images
async def handle_image(update: Update, context:
ContextTypes.DEFAULT_TYPE):
    # Check if the message contains a photo
    if update.message.photo:
        # Get the highest resolution photo
        photo = update.message.photo[-1]
        # Get the file object
        file = await photo.get_file()
        # Define the file path to save the image
        file_path = os.path.join(DOWNLOAD_FOLDER,
f"{file.file_id}.jpg")
        # Download the image
```

```
        await file.download_to_drive(file_path)
        # Notify the user
        await update.message.reply_text(f"Image saved as {file_path}")

        try:
            # Predict the class of the image
            predicted_class, confidence = predict_image_class(file_path)
            if confidence > 0.55:  # Check if confidence is greater than 70%
                await update.message.reply_text(f"Predicted class:
{predicted_class} (Confidence: {confidence:.2f})")
            else:
                await update.message.reply_text("Wrong image: Confidence is
too low.")
        except Exception as e:
            await update.message.reply_text(f"Error processing image: {e}")
    else:
        await update.message.reply_text("Please send an image.")

# Main function to start the bot
def main():
    # Create the application
    application = Application.builder().token(BOT_TOKEN).build()

    # Add a handler for images
    application.add_handler(MessageHandler(filters.PHOTO,
handle_image))

    # Start the bot
    print("Bot is running...")
    application.run_polling()

if __name__ == "__main__":
    main()
```

ANNEXURE 2
PLAGIARISM REPORT

MobileNet MobileNet

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ANNEXURE 3
CONFERENCE ACCPTENCE

Acceptance for the Conference- ICITSM-25

conference@icitsm.com
to me, aarthirithvik03, madona.se

Dear Shanmukha Sai .N, Aarthi. E, Dr. Madona B Sahaai

We're happy to inform you that your paper has been accepted for presentation at the
4th International Conference on Information Technology, Civil Innovation, Science, and Management (ICITSM-25), scheduled to be held on April 28–29, 2025.

Paper ID: ICITSM - 739
Paper Title: MobileNet Neural Network skin disease detector with Raspberry pi Integrated to Telegram