SKIN CANCER CLASSIFICATION USING DEEP LEARNING

A PROJECT REPORT

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE
OF

MASTER OF TECHNOLOGY (M. TECH)
IN

ARTIFITIAL INTELLIGENCE

Submitted by

CHANDAN KUMAR

2K22/AFI/05

Under the Supervision of

Dr. PRASHANT GIRIDHAR SHAMBHARKAR

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi 110042

MAY, 2024

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering) Bawana Road, Delhi-110042

CANDIDATE'S DECLARATION

I, **Chandan kumar 2K22/AFI/05** students of M.Tech, hereby declare that the project Dissertation titled "**Skin Cencer Classification Using Deep Learning**" which is submitted by me to the **Department of Computer Science and Engineering, Delhi Technological University, Delhi** in partial fulfilment of the requirement for the award of degree of **Master of Technology**, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

Place: **Delhi** **Chandan Kumar**
Date: **2K22/AFI/05**

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering) Bawana Road, Delhi-110042

CERTIFICATE

I hereby certify that the Project Dissertation titled "**Skin Cencer Classification Using Deep Learning**" which is submitted by **Chandan Kumar, 2K22/AFI/05**, **Department of Computer Science and Engineering**, **Delhi Technological University, Delhi** in partial fulfillment of the requirement for the award of the degree of **Master of Technology**, is a record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: **Delhi**
Date:

Dr. Prashant Giridhar Shambharkar
Professor

ABSTRACT

Timely detection is paramount in the effective management of skin cancer, emphasizing the pivotal role of precise diagnostic tools. A resilient medical decision support system, proficient in categorizing skin lesions based on dermoscopic images, serves as a fundamental tool in assessing the prognosis of this condition. Despite the intricate manifestations across different forms of skin cancer, recent strides in Deep Convolutional Neural Networks (DCNN) have markedly bolstered the capability to discern diverse cancer types from dermoscopic imagery. These advancements in DCNNs have revolutionized the field of dermatology,[6]. enabling more accurate and efficient classification of skin lesions. By leveraging the power of deep learning, researchers have been able to develop models that can not only distinguish between benign and malignant lesions but also classify specific types of skin cancer with high accuracy. This level of precision is crucial in ensuring that patients receive timely and appropriate treatment, ultimately improving outcomes and reducing mortality rates associated with skin cancer[4]. Furthermore, the development of robust medical decision support systems based on DCNNs has the potential to alleviate the burden on healthcare professionals by providing them with reliable tools for assisting in diagnosis and treatment planning. As these technologies continue to evolve, they are likely to play an increasingly important role in the early detection and management of skin cancer, ultimately saving lives and improving patient care[4].

Numerous machine learning methodologies have emerged, aiming for refined skin cancer diagnosis leveraging medical images, with a notable reliance on pre-trained Convolutional Neural Networks (CNNs) to surmount the hurdle of limited training data. However, the scarcity of malignant tumor samples often constrains these models, impeding classification accuracy. This study's principal objective is to craft a model proficient in accurately distinguishing between melanoma and non-melanoma skin cancer variants[12]. To this end, we propose an optimized architecture rooted in NASNet, augmented by the integration of supplementary data and the inclusion of an additional foundational layer within the CNN framework. This proposed approach fortifies the model's adaptability to incomplete and disparate data instances, thereby advancing its efficacy in skin cancer classification[4].

The integration of supplementary data, such as clinical information and patient history[15][25],

serves to enrich the model's understanding of the context surrounding each image, enhancing its ability to make accurate classifications. Additionally, the inclusion of an additional foundational layer within the CNN framework allows the model to capture more intricate patterns and features within the data, further improving its classification performance. By combining these elements with the powerful architecture of NASNet, we aim to develop a model that not only achieves high accuracy in distinguishing between melanoma and non-melanoma skin cancer but also demonstrates robustness in handling variations and complexities within the dataset[4].

Moreover, the proposed approach holds promise for addressing the challenge of limited training data by enhancing the model's ability to generalize from the available samples. By improving the model's adaptability to incomplete and disparate data instances, we aim to create a more resilient and effective tool for skin cancer classification. This study contributes to the ongoing efforts in leveraging machine learning and deep learning techniques for enhancing medical diagnostics, particularly in the field of dermatology[6].

ACKNOWLEDGEMENT

I am extremely grateful to my project guide, Dr. Prashant Giridhar Shambharkar, Professor, Department of Computer Science and Engineering, Delhi Technological University, Delhi for providing invaluable guidance and being a constant source of inspiration throughout my research. I will always be indebted to him for the extensive support and encouragement he provided. I am highly indebted to the panel faculties during all the progress evaluations for their guidance, constant supervision and for motivating me to complete my project work. They helped me throughout by giving new ideas, providing necessary information and pushing me forward to complete the project work.

CHANDAN KUMAR
(2K22/AFI/05)

Table of Contents

CANDIDATE'S DECLARATION .... **ii**
CERTIFICATE .... **iii**
ABSTRACT .... **iv**
ACKNOWLEDGEMENT .... **vi**
LIST OF FIGURES **8**
CHAPTER 1 .... **9**
INTRODUCTION ***9***
1.1 Overview 9
CHAPTER 2 .... **13**
LITERATURE REVIEWS ***13***
CHAPTER 3 .... **25**
METHODOLOGY ***25***
3.1 Dataset Overview 25
3.2 Image Pre-Processing 29
3.3 Visual Reshaping 32
3.4 Data Augmentation 33
3.5 Pre-configured Neural Network 36
3.6 Performance Evaluation 41
CHAPTER 4 .... **51**
CONCLUSION ***51***
REFERENCES **55**

LIST OF FIGURES

- Fig 1.0 Class Levels images
- Fig 2.0 Optimization of NASNet Model
- Fig 2.1 Relationship Between Training Epochs
- Fig 2.2 Relationship Between Training Epochs and Loss in NASNet Large
- Fig 2.3 Evaluating ROC Curve Performance for NASNet Mobile using Adam Optimizer

CHAPTER 1

INTRODUCTION

1.1 Overview

The skin is the largest organ in the body, averaging fifteen percent of the total weight of a person's whole body, and an area of twenty square feet. It has three significant layers: the dermis, hypodermis, and epidermis. The three layers together have very significant roles in the general health of a person. Skin, as a part of the integumentary system, gives the body a strong barrier against many outer threats: physical damage, microbiological infections, ultraviolet radiation, and many other atmospheric pollutions. To this, add the sensory function through the myriad of nerve endings, the type of sensation giving the opportunity to control the body temperature by perspiration and widening the blood vessels, and the adjustment of the body at just the right level of hydration by avoiding the loss of water through the dermis. Melanocytes are special cells in the epidermis that are actively secreting melanin, a pigment coloring the skin and the hair. They may also play a role in absorbing UV radiation and thus "protecting" the skin, reducing the risks of DNA mutations in skin cells that otherwise would cause skin cancers. In turn, the possibility of underlying the protective epidermis itself is a subject to disease, among which is cancer, that is characterized by uncontrolled growth of abnormal cells. In fact it gives essential skin protection. This dysregulation can develop into malignant tumors and become life-threatening, particularly if they metastasize to locations elsewhere in the anatomy. One of the most common kinds of cancer is Skin cancer. Skin cancer is described as the concept where skin cells grow uncontrollably as they replicate into either a sore or a tumor. According to Melanoma [6], squamous cell carcinoma, basal cell carcinoma, and the World Health Organization (WHO), these are the most common types of skin cancer, and in combination, they are estimated to register millions of cases around the world every year. So, the increasing incidence of the disease in recent decades implies the importance of the detection, prevention, and treatment strategy against skin disease in general in the overall health of the skin, the reduction of risk for skin cancers, and the prevention of mortality.

All of this against a backdrop of concern; it has become urgent to attend to raising awareness and the implementing of preventive measures. The risk factors for skin cancer have been well identified, including those that are potentially modifiable: sun exposure during leisure activities, use of tanning beds, previous incidents of sunburn, etc. [1] To reduce the burden of

this disease significantly, the general public needs to be made acutely aware of these factors And urged to take precautions to prevent damage to their skin through harmful ultraviolet radiation. [3] Public education programs would need to emphasize the use of broad-spectrum high SPF sunscreen and seeking shade during the hot sun hours, wearing protective clotthing, including hats and sunnglasses, and avoidiing tanning beds. Most importantly, early diagnosis, if there were diseases such as skin malignancies, would provide better treatment and management among the patients. Indeed, the health care provider himself is very instrumental in providing information to his knowledge-hungry patients on the risks and benefits of preventive measures against the evils of the UV rays of the sun. Community programs and public health drives have to initiate a step in increasing public awareness of and access to sun protection mechanisms. This could bring the number of cases of skin cancer down, raise awareness of a healthy skin culture, and inculcate proactive behavior; hence, it will have significant and relevant public health with less burden on health systems.

The diagnostic work-up of skin cancer usually consists of a complete physical examination, a noninvasive dermoscopic examination, and either biopsy or excision of suspicious lesions, followed by microscopic examination to classify them concerning their malignancy status. The subsequent evaluation may be required for the design of the extent and nature of the malignancy to guide the structuring of appropriate therapeutic modalities. These protocols most often include imaging protocols consisting of CT, MRI, or PET scans for determining if the cancer has metastasized. Accurate staging of skin cancer is, hence very important in deciding the treatment plan.

The approach of management depends on the type and the stage of the cancer but includes: • Immunotherapy, Chemotherapy, Radiation treatment, Surgery. Surgical removal of skin cancers remains the mainstay of management of early skin cancers. Savvy ways of doing closure are part of Mohs surgery, in which the surgeon eliminates as little healthy tissue as possible through the excision of all cancerous tissue. It is effective for some types of skin cancer. Often, multimodal approaches are called for more advanced cases or when the cancer has spread beyond the skin. Radiation therrapy may be applied to destroy those cancer cells that are not surgically removable. Administration could take the form of chemotherapy, which uses drugss to destroy fast-growiing cells when the cancar has metastasized to other organs. Another concept, immunotherapy, uses one's immune system to rid the cancer cells, and new advancements in treatment promise to give advanced melanoma patients and other skin cancers new hope.

The type and stage of the cancer, other general health considerations, the existence of different conditions, general well-being, and the existence of specific genetic mutations in the cells that have become cancerous are all factors that can influence the treatment modality. Personalized medicine has recently made revolutionary advances. It is now being translated into new targeted therapies by singling out the specific molecular pathways implicated in the Growth and survival of cencer cell.

This could be achieved because it would provide a more personalized and, hence improved treatment approach. These efforts will increase the rates of survival in the case of skin cancer patients by reducing the chances of recurrence and enhancing the quality of life. While new therapies and combinations are constantly being explored, new research brings hope for even more advanced treatments.

The last years have brought a breakthrough in this critical area of dermatology: deep learning in combination with machine learning approaches. Nowadays, the classification and categorization of skin cancer have become relatively easy. Recently, even machine learning-based approaches are switching to Support Vector Machines, Decision Trees, and Deep Learning algorithms since they are becoming significantly essential analytical tools for researchers dealing with the growing pool of dermatological images.

Image processing methods will play a key role in cancer classification because they can enhance the legitimacy of an image and further segment it into relevant regions, from which the extraaction of pertinent featurres is appropriate for the accurate clasification of cancer. These techniques, packed between the primary dimensionality reduction techniques, are of great help in proper classification using ML and DL models, offering clear advantages compared to the traditional modes of diagnosis.

Most important, high levels of automation for such processes decrease the reliance on human perception and improve the timeline for diagnosis such that the patient gets an accurate diagnosis. This will be a game changer in patient outcomes, especially in low-resource setting Where a diagnosis is required urgently.

CHAPTER 2

LITERATURE REVIEWS

Skin cancer remains a major global public health issue, highlighting the necessity for a thorough understanding of its causes, risk factors[1] and diagnostic methods to manage the disease effectively. Various factors, including genetic predisposition, environmental influences, and lifestyle choices, contribute to the development of skin cancer. Gandhi and Kampp provide valuable insights into the epidemiology,detection, and management of skin cancer, emphasizing the crucial role of early detection in improving patient outcomes.[2] Their research explores the different forms of skin cancer, including basal cell carcinoma, squamous cell carcinoma, and melanoma, each with unique characteristics and prognoses. The authors stress the importance of public awareness campaigns and educational programs to equip individuals with the knowledge to recognize early signs and symptoms of skin cancer, facilitating prompt medical intervention. Additionally, Harrison and Bergfeld draw attention

,

Athletes face a heightened risk of skin cancer due to prolonged exposure to ultraviolet (UV) light during outdoor activities[3]. Those involved in sports such as running, cycling, and swimming spend extensive periods in the sun, increasing their vulnerability to UV-induced skin damage. This underscores the importance of preventive measures, including regular skin screenings and sun protection practices, to reduce the risk of skin cancer in this group. The authors recommend that sports organizations and athletic associations play a vital role in promoting sun safety by offering resources and guidelines on effective sun protection strategies, such as using broad-spectrum sunscreens, wearing protective clothing, and scheduling training sessions during times of lower UV exposure. Moreover, the role of healthcare professionals in the early detection and management of skin cancer is crucial. Dermatologists, primary care physicians, and oncologists need to be proficient in the latest diagnostic techniques and treatment options to offer the best care for patients. Advances in dermoscopy, biopsy methods[11][13], and imaging technologies have greatly improved the precision of skin cancer diagnoses, allowing for customized treatment plans that improve patient outcomes.[11][13] The use of artificial intelligence and machine learning in dermatology also shows potential for enhancing diagnostic accuracy and streamlining the identification of malignant lesions[6].

These findings highlight the necessity of continuous research and Public health campaigns aimed to increase knowledge, encourage early detection, and implementing preventive measures to lessen the global burden of skin cancer. Collaboration among researchers, healthcare providers, policymakers, and the public is crucial for developing and spreading effective skin cancer prevention and management strategies. Public health campaigns should aim to educate people about the risks of UV exposure, the importance of regular skin checks, and the benefits of protective measures. By encouraging a proactive approach to skin health, we can reduces the inciidence and impect of skins cancer, ultimattely improviing the quallity of life worldwide.

The American Academy of Dermatology and JAMA Dermatology offer valuable statistics on skin cancer, including estimates of its prevalence in the United States. According to their data, skin cancer remains one of the most common cancers, with millions of new cases diagnosed annually. Researchers like Whiteman, Green, and Olsen have projected a growing burden of invasive melanoma, stressing the urgent need for better diagnostic tools to manage rising incidence rates[5]. These projections highlight the importance of ongoing research and development in dermatology to enhance early detection and treatment strategies for skin cancer.The data from these sources highlight the critical need for public health initiatives focused on skin cancer prevention, education, and early detection to reduce the impact of this disease on individuals and healthcare systems. Effective public health campaigns can play a pivotal role in educating the populace about the risks associated with UV exposure, the importance of regular skin checks, and the benefits of protective measures such as sunscreen use and wearing protective clothing.

In response to the pressing need for more effective tools in diagnosing skin cancer, researchers such as Xie et al. and Dalila et al. have delved into the possibilities offered by neural network models and image segmentation techniques.[8] Their work represents a significant stride in the field, as these technologies hold the promise of enhancing the classification of melanoma and benign skin lesions. By harnessing the power of neural networks, which are capable of learning complex patterns from data, and employing advanced image segmentation techniques to isolate key features in images, these studies have yielded promising results.[8] The neural networks are designed to analyze vast amounts of data, identifying subtle differences between malignant and benign lesions that may be difficult for human eyes to detect. Image segmentation techniques[8], on the other hand, allow for precise isolation of the lesion from the surrounding skin, improving the accuracy of the analysis.

These advancements not only offer the potential for more accurate and efficient diagnoses but also hold the promise of improving patient outcomes by enabling earlier detection and intervention. Early detection of skin cancer is crucial, as it significantly increases the chances of succesful tretment and reduces the likelihod of the cancer sprading to other parts of the body. By incorporating these technological advancements into clinical practice, the medical community could revolutionize the way skin cancer is diagnosed and managed, potentially reducing the need for invasive procedures such as biopsies and improving overall patient care. Furthermore, the integration of these technologies into routine dermatological practice could streamline the diagnostic process, making it faster and more accessible for patients[14][30].

As such, the work of Xie et al. and Dalila et al. represents a crucial step forward in the fight against skin cancer, underscoring the importance of ongoing research and innovation in this field. Their studies pave the way for future developments that could further enhance the accuracy and efficiency of skin cancer diagnosis, ultimately leading to better patient outcomes. The collaboration between technology experts and medical professionals is essential to ensure that these advancements are effectively translated into clinical practice. By continuing to invest in research and development, we can hope to see significant improvements in the early detection and management of skin cancer, ultimately reducing the burden of this disease on individuals and healthcare systems worldwide[14][25].

Dermoscopy and biopsy continue to play a fundamental role in the diagnosis of skin cancer. Researchers such as Bomm et al.[11][13]. and Kato et al. have extensively explored the utility of dermoscopy-guided biopsy and dermoscopy in diagnosing various skin cancers, including melanoma[6]. Dermoscopy, a non-invasive imaging technique, allows for a closer examination of skin lesions, providing detailed visualization of subsurface structures that are not visible to the naked eye. This capability is particularly beneficial in the early detection of melanoma and other skin cancers, as it enables clinicians to identify malignancies at a stage when they are most treatable. By revealing features such as pigmentation patterns, vascular structures, and lesion asymmetry, dermoscopy enhances diagnostic accuracy and reduces the likelihood of unnecessary biopsies[12][28].

Dermoscopy-guided biopsy, on the other hand, involves using dermoscopy to pinpoint the most suspicious areas of a lesion for biopsy, thereby improving the accuracy and diagnostic yield of the procedure. This method ensures that the biopsy samples are taken from the regions most likely to contain malignant cells, which can significantly increase the likelihood of an accurate diagnosis[11][13]. The research conducted by Bomm et al. and Kato et al.[11][13], underscores the importance of incorporating dermoscopy into clinical practice for more precise and efficient skin cancer diagnosis. Their findings advocate for the widespread adoption of these techniques, highlighting their potential to enhance clinical outcomes by facilitating earlier and more accurate detection of skin cancer[12][28].

In addition to advancements in diagnostic techniques, Gershenwald et al. provide an evidence-based update on melanoma staging, reflecting the latest changes in staging guidelines and enhancing clinical management strategies[14][25]. Staging is a critical component of melanoma diagnosis, as it determines the extent of the disease and guides treatment decisions. The updated guidelines introduced by Gershenwald et al. offer clinicians a more comprehensive and accurate framework for staging melanoma, incorporating advancements in diagnostic technologies and a deeper understanding of the disease's progression. These new guidelines include refined criteria for tumor thickness, ulceration status, and the presence of metastasis, all of which are crucial factors in determining the stage of melanoma and the appropriate therapeutic approach.

The work of Gershenwald et al. underscores the importance of staying abreast of evolving guidelines and incorporating them into clinical practice to improve patient outcomes[14][25]. Their research highlights the necessity for continuous education and adaptation in the medical field, ensuring that clinicians are equipped with the most current knowledge and tools to manage skin cancer effectively. This update is particularly significant as it provides a more nuanced understanding of melanoma[6], enabling more personalized and effective treatment plans that can lead to better prognoses for patients.

Overall, the efforts of researchers like Bomm et al., Kato et al., and Gershenwald et al. highlight the ongoing advancements in the field of dermatology aimed at improving the accuracy and efficacy of skin cancer diagnosis and management. Their work demonstrates the critical importance of integrating advanced diagnostic techniques and updated staging guidelines into routine clinical practice[14][25]. These innovations ultimately benefit patients by enabling timely and appropriate interventions, reducing the morbidity and mortality associated with skin cancer, and enhancing the overall quality of care. The continued research and development in this field hold promise for even greater improvements in the future, underscoring the dynamic and evolving nature of dermatological science[30].

In the realm of technology and data analytics, Rahman et al. underscore the significance of machine learning in diagnosing clinical diseases[14][25]. Their work highlights the potential of machine learning algorithms to analyze complex datasets and identify patterns that can assist in the early and accurate diagnosis of various diseases, including skin cancer. This demonstrates the transformative impact of machine learning on healthcare, offering more personalized and efficient diagnostic approaches. Machine learning models, through their ability to process vast amounts of data quickly and accurately, can uncover subtle patterns and correlations that might be missed by traditional diagnostic methods. These algorithms can be trained on large datasets comprising medical images, patient histories, and genetic information, enabling them to predict disease outcomes and recommend appropriate treatment plans with a high degree of precision. Rahman et al. emphasize the importance of continuous training and updating of these models to keep pace with the evolving medical knowledge and ensure their effectiveness in real-world clinical settings[14][25].

Concurrently, Bazgir et al. draw attention to the critical importance of security considerations in IoT-based cloud computing, particularly in healthcare data management. The integration of Internet of Things (IoT) devices with cloud computing has revolutionized healthcare[15][1 9] . by enabling remote monitoring and data collection. This technology facilitates continuous health monitoring, allowing for real-time dataa transmision from wearabl devicess to healthcare providers, thereby improving patient care and outcomes. However, ensuring the security and privacy of this data is paramount, especially considering the sensitive nature of healthcare information. Bazgir et al.'s work highlights the need for robust security measures to protect healthcare data in IoT-based cloud environments. They talk about a variety of security risks, including cyberattacks, illegal access, and data breaches.and propose comprehensive strategies to mitigate these risks. These strategies include encryption, secure authentication protocols, and regular security audits to safeguard patient information and maintain trust in digital healthcare solutions[19].

Moreover, Ibtisum et al. delve into the optimization of big data processing, which is essential for handling the vast amounts of data generated in healthcare settings. Their research focuses on developing efficient algorithms and frameworks for processing and analyzing big data, enabling healthcare providers to obtain insightful knowledge and make wise selections based on large datasets. Enhancing patient care, increasing diagnostic accuracy, and advancing medical research all depend on the ability to handle and interpret large amounts of data efficiently. Ibtisum et al. explore various techniques, such as parallel processing, machine learning, and cloud-based solutions, to optimize the performance and scalability of big data systems. Their work addresses the challenges of data heterogeneity, volume, and velocity, proposing innovative solutions to streamline data integration and analysis processes. By enhancing the capability to process and interpret big data, healthcare providers can leverage these insights to predict disease outbreaks, personalize treatment plans, and improve overall healthcare delivery.

The combined efforts of these researchers illustrate the profound impact of technology and data analytics on modern healthcare.[18] The integration of machine learning, IoT, and big data processing holds the potential to revolutionize the way diseases are diagnosed, monitored, and treated. Rahman et al.'s exploration of machine learning algorithms for disease diagnosis highlights the potential for more accurate and timely interventions, while Bazgir et al.'s focus on security in IoT-based cloud computing underscores the importance of protecting sensitive healthcare data in an increasingly digital world. Ibtisum et al.'s work on optimizing big data processing further emphasizes the necessity of efficient data management techniques to harness the full potential of the information generated in healthcare environments.Together, these advancements promise to enhance patient outcomes, streamline healthcare operations, and pave the way for a more connected and data-driven health care

In a related vein, Molla et al. explore the utilization of social media data for understanding public sentiment during pandemics. Social media platforms, such as Twitter, Facebook, and Instagram, have emerged as valuable sources of real-time data that can provide deep insights into public perceptions and behaviors during health crises. The work of Molla et al. demonstrates how analyzing social media data can complement traditional public health surveillance methods, offering a more comprehensive and nuanced understanding of public sentiment. During pandemics, timely information is crucial for effective public health response, and social media provides a unique avenue for capturing the public's immediate reactions, concerns, and misinformation trends.

By employing advanced data analytics and natural language processing (NLP) techniques, Molla et al. have shown that it is possible to sift through vast amounts of social media posts to identify prevailing sentiments, misinformation, and public compliance with health guidelines[18]. This approach allows public health officials to gauge the effectiveness of communicationstrategies and make real-time adjustments to address public concerns and misconceptions[19]. The ability to track changes in sentiment over time also helps in predicting potential behavioral trends, such as vaccine acceptance or resistance, adherence to social distancing measures, and the overall public response to new health policies.

Furthermore, the integration of social media data with traditional epidemiological data can enhance the predictive modeling of disease spread and the allocation of healthcare resources. Molla et al. highlight that during the COVID-19 pandemic, social media data provided early warnings about outbreaks and public response patterns, which were instrumental in shaping timely and targeted public health interventions. This integration helps in creating a more dynamic and responsive public health infrastructure that can quickly adapt to changing circumstances and effectively manage crises.

Moreover, Molla et al.'s research underscores the importance of addressing the challenges associated with using social media data, such as ensuring data privacy, managing data quality, and dealing with the spread of misinformation. They emphasize the need for robust ethical guidelines and advanced algorithms to filter out noise and focus on relevant, accurate data. The insights gained from social media analytics must be contextualized and validated against reliable sources to ensure they are actionable and beneficial for public health efforts.

Together, these studies highlight the diverse applications of technology and data analytics in healthcare,[18] showcasing their potential to transform various aspects of the field, from diagnosis and data management to public health surveillance. The work of researchers like

Rahman et al., Bazgir et al., Ibtisum et al., and Molla et al. collectively demonstrates how leveraging technological advancements and data-driven approaches can lead to significant improvements in healthcare delivery and public health outcomes. By integrating machine learning for disease diagnosis, ensuring the security of IoT-based health data, optimizing big data processing, and utilizing social media for public sentiment analysis, these innovations pave the way for a more efficient, responsive, and patient-centered healthcare system. As the healthcare landscape continues to evolve, the incorporation of these advanced technologies and methodologies will be crucial in addressing current and future challenges, ultimately enhancing the quality of care and the resilience of public health systems.

Furthermore, studies by Ahmmed et al., Sarker et al., and Alam et al. demonstrate the integration of AI, IoT, and deep learning in healthcare, offering innovative solutions for disease diagnosis and management. These advancements showcase the potential of deep learning techniques, particularly in the realm of healthcare, including the diagnosis of skin cancer. Integrating these technologies could revolutionize healthcare by enabling more accurate, efficient, and personalized care. Ahmmed et al. have focused on using AI algorithms to analyze medical images and patient data, significantly enhancing diagnostic accuracy and facilitating early disease detection. IoT devices collect real-time data from patients, allowing continuous monitoring and early identification of potential health issues. This integration reduces the need for frequent hospital visits and allows for remote monitoring, which not only improves patient outcomes but also lessens the strain on healthcare systems.

Sarker investigate deep learning's role in predicting disease progression and personalizing treatment plans. Their work highlights how AI can be used to build customized treatment plans by analyzing large, complicated datasets that include genetic, lifestyle, and environmental aspects.

By tailoring care to each patient's specific needs, this individualized approach increases the effectiveness of medical interventions and lowers their side effects.Deep learning models, capable of learning from vast data, are particularly adept at identifying patterns and making predictions that can inform clinical decision-making.Alam et al. further delve into the development of AI-driven diagnostic tools that assist healthcare professionals in making more informed decisions. Their studies demonstrate how AI can augment the capabilities of healthcare providers by offering second opinions, identifying potential diagnostic errors, and

AI and human expertise enhances the overall quality of care and ensures that patients receive accurate and timely diagnoses.

In the realm of skin cancer diagnosis, Esteva et al. have made significant strides by demonstrating the capabilities of deep neural networks to achieve dermatologist-level classification of skin cancer. Their research involves training deep learning models on large datasets of labeled skin images, enabling the models to recognize various types of skin lesions with high accuracy. This advancement holds promise for improving early detection and treatment of skin cancer, as these AI systems can assist dermatologists in identifying malignant lesions that might otherwise go unnoticed.

Moreover, Ioffe and Szegedy's work on batch normalization techniques plays a crucial role in accelerating the training of deep networks. Batch normalization addresses the issue of internal covariate shift, which can slow down the training process of deep neural networks. By normalizing the inputs of each layer, this technique ensures that the training process is more stable and efficient, allowing for the development of more accurate and robust AI models in a shorter period. The combination of batch normalization with deep learning techniques enables the creation of powerful diagnostic tools that can be deployed in clinical settings to assist healthcare professionals in making quick and accurate diagnoses[29].

These studies collectively highlight the transformative potential of integrating AI, IoT, and deep learning in healthcare. Healthcare practitioners can optimize patient outcomes, tailor treatment programs, and improve diagnostic accuracy by utilizing new technologies.The work of Ahmmed et al., Sarker et al., Alam et al., Esteva et al., and Ioffe and Szegedy underscores the importance of ongoing research and innovation in this field. As these technologies continue to evolve, they promise to address some of the most pressing challenges in healthcare, ultimately leading to a more efficient, effective, and patient-centered healthcare system.

Moreover, recent research by Mishra et al., Mijwil, Romero Lopez et al., Thurnhofer-Hemsi et al., Nugroho et al., Mehra et al., and Ismail et al. further pushes the boundaries of the field by exploring fine-grained dermatological classification, skin cancer image classification, and transfer learning approaches for skin cancer diagnosis. These studies contribute to a growing body of literature that demonstrates the potential of AI and deep learning in revolutionizing healthcare, particularly in the field of dermatology. Each of these research efforts highlights different aspects and techniques that collectively enhance our understanding and capability in diagnosing skin conditions with unprecedented accuracy.

Mishra et al. delve into fine-grained dermatological classification, focusing on the ability to distinguish between very similar skin conditions that often present overlapping symptoms[30]. This level of precision is crucial for dermatologists as it aids in identifying the most appropriate treatment options for specific skin conditions. By using advanced deep learning models, the researchers have been able to achieve high levels of accuracy in distinguishing between conditions such as different types of dermatitis, psoriasis, and eczema, which are often challenging to differentiate based on visual inspection alone.

Mijwil's work emphasizes skin cancer image classification, where Enhancing the identification and categorization of skin cancer, including melanoma, basal cell carcinoma, and squamous cell carcinoma, is the main objective.By training deep neural networks on large, annotated datasets of skin images, Mijwil has contributed to the development of models that can detect malignancies with a precision that rivals human dermatologists. This research is particularly impactful as early detection of skin cancer is critical for successful treatment and patient survival rates[6].

Romero Lopez et al. and Thurnhofer-Hemsi et al. explore the use of transfer learning approaches in skin cancer diagnosis. Transfer learning involves taking a pre-trained model, often trained on a large dataset from a different but related task, and fine-tuning it on a specific dermatological dataset[30]. This approach is highly efficient as it leverages the knowledge the model has already acquired, thus requiring less training data and computational resources. Their studies have shown that transfer learning can significantly enhance the performance of skin cancer diagnostic models, making them more robust and capable of generalizing better to new, unseen data.[35][24][20]

Nugroho et al. and Mehra et al. focus on the integration of AI and deep learning technologies in practical, clinical settings. Their research involves developing user-friendly diagnostic tools that can be used by dermatologists and general practitioners to aid in the early detection and treatment of skin conditions. These tools often incorporate features such as real-time image analysis, predictive analytics, and decision support systems, which can provide clinicians with valuable insights and recommendations, thereby improving patient care and outcomes.

Ismail et al. further extend the application of deep learning in dermatology by investigating the potential of these technologies in underserved and remote areas. Their research highlights the feasibility of deploying AI-powered diagnostic tools in low-resource settings where access to specialized dermatological care is limited. By using mobile devices and cloud-based solutions, Ismail et al. have demonstrated that it is possible to provide high-quality dermatological care to populations that would otherwise have limited access to such services. These collective efforts by Mishra et al., Mijwil, Romero Lopez et al., Thurnhofer-Hemsi et al., Nugroho et al., Mehra et al., and Ismail et al. underscore the transformative impact of AI and deep learning in the field of dermatology. By leveraging these advanced technologies, researchers and healthcare practitioners can enhance diagnostic accuracy, improve patient outcomes, and ultimately, advance the field of dermatological care[30]. The integration of AI- driven solutions into clinical practice holds great promise for addressing current challenges in dermatology, including the accurate and timely diagnosis of skin conditions, the provision of personalized treatment plans, and the extension of dermatological services to remote and underserved areas. As this body of research continues to grow, it paves the way for a future where AI and deep learning are integral components of dermatological practice, significantly improving the quality of care and patient satisfaction[30].

In the broader context of disease diagnosis, Podder et al. and Mondal et al. present deep learning frameworks that showcase the versatility of deep learning in addressing various healthcare challenges. Podder et al. focus on diagnosing infectious lung diseases, demonstrating the potential of deep learning in analyzing medical images to identify and classify patterns associated with these diseases. Their framework offers a promising approach to improving the accuracy and efficiency of diagnosing infectious lung diseases[37], which can significantly impact patient outcomes and healthcare resource utilization. By leveraging convolutional neural networks (CNNs) and other advanced machine learning techniques, Podder et al. have developed models capable of detecting diseases such as tuberculosis, pneumonia, and other respiratory infections with high precision. This is particularly important in the context of infectious diseases, where early and accurate diagnosis can lead to timely treatment and prevent the spread of infections. The ability to quickly and accurately diagnose lung infections not only improves patient care but also helps in the effective allocation of healthcare resources, reducing the burden on healthcare systems.

On the other hand, Mondal et al. highlight the application of deep learning in screening for COVID-19, a pressing global health concern. Their work illustrates how deep learning models can be trained on chest X-ray images to detect signs of COVID-19, providing a rapid and scalable screening solution. The COVID-19 pandemic has underscored the need for efficient and reliable diagnostic tools that can be deployed on a large scale to manage and control the spread of the virus. Mondal et al.'s deep learning framework addresses this need by offering a tool that can quickly analyze chest X-rays and identify COVID-19-related abnormalities with a high degree of accuracy. This approach not only speeds up the screening process but also ensures that limited testing resources can be directed towards the most likely cases, enhancing the overall efficiency of pandemic response efforts.

These studies underscore the broad applicability of deep learning in healthcare, showcasing its potential to revolutionize disease diagnosis and management across a range of medical conditions. The work of Podder et al. and Mondal et al. demonstrates how deep learning can be utilized to tackle some of the most challenging aspects of disease diagnosis, from identifying complex patterns in medical images to providing rapid screening solutions in the face of global health emergencies. By applying these advanced technologies, healthcare professionals can achieve greater diagnostic accuracy, reduce diagnostic delays, and ultimately improve patient outcomes.

Furthermore, the frameworks developed by Podder et al. and Mondal et al. exemplify the adaptability of deep learning models to various medical imaging modalities and disease contexts. Whether it is the detailed analysis of lung images for infectious diseases or the swift screening for COVID-19, these models can be tailored to meet specific diagnostic requirements. This adaptability is crucial for addressing the diverse and evolving challenges in healthcare, making deep learning an indispensable tool in modern medical practice[37][38].

In addition to improving diagnostic processes, the implementation of deep learning in healthcare also facilitates the continuous improvement of medical knowledge. As these models are exposed to more data over time, they can learn and adapt, becoming more accurate and robust in their predictions. This continuous learning process ensures that deep learning models remain at the cutting edge of medical diagnostics, providing healthcare professionals with the most advanced tools available.

Overall, the research by Podder et al. and Mondal et al. highlights the transformative impact of deep learning on healthcare, demonstrating its capacity to enhance disease diagnosis and management significantly. As deep learning technologies continue to evolve, their integration into healthcare systems promises to bring about more efficient, accurate, and scalable solutions for diagnosing a wide range of medical conditions. This evolution is poised to revolutionize the field of healthcare, offering new avenues for improving patient care and optimizing healthcare delivery worldwide[39][37].

CHAPTER 3

METHODOLOGY

In this section, the proposed methodology is detailed, and the approach and techniques underlined below are explained. In this methodology, both the machine learning algorithms and the image processing techniques are used to fulfill the research objectives. The paper is detailed with a preprocessed dataset of dermatological images of skin lesions and moles. The pre-processing involves enhancement of the image quality and removal of the noise present within the data to make it appropriate for analysis. This is followed by the process of extracting features from the images, which will, in turn, give the relevant textures, colors, and shape characteristics used in the classification of skin lesions. Features are then fed into the machine learning algorithms, and the most effective in classifying images have been those using convolutional neural networks[33]. Therefore, the models are trained on this dataset to learn patterns and relationships so that they can make the proper classification of skin moles and lesions as either malignant or benign. Finally, the study of the performance measures will be put up against the cross-validation techniques to ensure robustness. This methodology will help the health care professional in diagnostic accuracy with a better decision about patient care in a methodical, effective way for the classification of skin lesions and moles..

3.1 Dataset Overview

The effectiveness of deep learning methodologies depends on a well-suited and meticulously validated dataset. In this study, the dataset includes 2637 dermoscopic images, with 1197 depicting malignant lesions and 1440 showing benign conditions. Each image is linked to a unique patient identifier, ensuring data integrity throughout the analysis. This detailed association allows precise data tracking and management, essential for maintaining the study's reliability and accuracy.

The dataset is carefully balanced, with an equitable representation of both benign and malignant classes. This balance is crucial for training machine learning models to avoid bias, enhancing their ability to accurately classify unseen data. An imbalanced dataset could result

The dataset's careful curation involves rigorous validation to ensure image quality and consistency. Each dermoscopic image is scrutinized for clarity, resolution, and relevance to the study's objectives. This meticulous approach ensures that the dataset consists of high-quality images that accurately represent the range of dermatological conditions being studied. Such thorough validation is critical for training deep learning models, as high-quality input data directly impacts the model's accuracy and reliability.In addition to balancing the classes and validating the image quality, the dataset includes a diverse range of skin types and lesion characteristics. This diversity is essential for developing a model that can generalize well across different populations and dermatological conditions. By incorporating images from patients of varying ages, genders, and ethnic backgrounds, the study aims to create a model that is not only accurate but also widely applicable in clinical settings. This comprehensive approach to dataset curation helps ensure that the model can effectively classify skin lesions in a diverse patient population, thereby improving its utility and relevance in real-world scenarios.

The detailed annotation of each image with relevant metadata, including patient demographics and clinical information, further enriches the dataset. This additional information provides valuable context for the deep learning models, allowing them to learn from not just the visual features of the lesions but also the associated clinical characteristics. Integrating such contextual data can enhance the model's ability to make nuanced and accurate predictions, leading to better diagnostic outcomes.

The meticulous curation and validation of this dataset lay a solid foundation for the study's deep learning approach to effectively classify skin lesions. The balanced representation of benign and malignant conditions, coupled with rigorous quality checks and diverse patient data, ensures that the resulting model is both accurate and generalizable. By leveraging this robust dataset, the study aims to develop a deep learning model that can significantly improve diagnostic accuracy in dermatology, ultimately contributing to better patient care and outcomes. This thorough and systematic approach to dataset preparation underscores the importance of high-quality data in the successful application of deep learning in healthcare, highlighting how meticulous data curation can drive advancements in medical diagnostics.

To further enhance the robustness of the dataset, a series of data augmentation techniques were meticulously employed. These techniques included rescaling, width shifting, rotation, adjustment of shear ranges, horizontal flipping, and channel shifting. Rescaling ensures that images are uniformly sized, which is essential for training deep learning models. Uniform image size allows the model to process the data consistently, avoiding discrepancies that could arise from varying dimensions. This standardization is crucial for the convolutional layers of deep learning architectures to perform optimally.

Width shifting and rotation introduce variations in the position and orientation of the lesions, mimicking real-world scenarios where skin lesions may appear at different angles. These transformations help the model learn to recognize lesions regardless of their position within the image frame, enhancing the model's robustness and ability to generalize to new, unseen images. By simulating these positional variations, the model becomes adept at identifying lesions from diverse perspectives, thereby improving its diagnostic accuracy.

Adjusting shear ranges helps simulate the distortion that can occur in images taken from different angles or perspectives. Shearing alters the shape of the image, creating a slanting effect that is often seen in clinical photography due to variations in camera angles and patient positioning. Incorporating shear transformations into the dataset trains the model to handle such distortions effectively, ensuring that it can accurately classify lesions even when the images are not perfectly aligned.

Horizontal flipping creates mirror images, increasing the diversity of the dataset and helping the model generalize better. This technique effectively doubles the number of training samples by generating flipped versions of existing images. The additional data helps the model learn the symmetrical properties of skin lesions, making it more robust to variations in appearance. This is particularly beneficial for conditions that may present differently on various parts of the body or for lesions that have a symmetrical structure.

Channel shifting involves randomly changing the color channels of the images, adding further variation to the dataset. This technique simulates changes in lighting conditions and camera settings that can affect the color representation of the images. By introducing variations in color channels, the model learns to identify lesions based on their structural and textural features rather than relying solely on color. This enhances the model's ability to generalize across images taken in different lighting conditions, improving its performance in real-world clinical environments.

In addition to these specific augmentation techniques, the overall strategy of data augmentation plays a crucial role in preventing overfitting, in which the model performs badly on new data because it is overly tailored to the training set. By presenting the model with a wide range of augmented images, it learns to recognize the fundamental features of skin lesions, making it more adaptable to variations and anomalies in new images. This leads to a more generalized and robust model that performs well on diverse datasets.

The careful implementation of these data augmentation techniques significantly enriches the dataset, making it more representative of the variety of conditions encountered in clinical practice. This comprehensive augmentation process ensures that the deep learning model is exposed to a broad spectrum of image variations, enhancing its learning process and improving its ability to accurately classify skin lesions. As a result, the model developed through this enhanced dataset is more reliable and effective, contributing to better diagnostic accuracy and ultimately advancing the field of dermatology.

By leveraging these data augmentation techniques, the study not only improves the quality and robustness of the dataset but also demonstrates the importance of comprehensive data preparation in the development of deep learning models. This meticulous approach to data augmentation underscores the commitment to achieving high diagnostic performance and reliability, highlighting how thoughtful and systematic data processing can drive significant advancements in medical diagnostics and patient care.

Notably, Figure 1 provides a selection of sample images, offering a visual depiction of the dataset's composition. This visualization aids in understanding the characteristics and diversity of the images, which is crucial for evaluating the deep learning model's performance. By meticulously employing data augmentation techniques and offering a visual representation of the dataset, the study ensures that the deep learning model is trained on a robust and diverse dataset, enhancing its ability to accurately classify skin lesions. The images in Figure 1 demonstrate the range of skin lesions in the dataset, showcasing various shapes, sizes, and textures commonly seen in clinical practice. This diversity is essential for training the model to recognize and differentiate between different types of lesions, ensuring it generalizes well to unseen cases. Additionally, the images highlight the impact of data augmentation, with variations in orientation, position, and color that simulate real-world scenarios. This augmented dataset challenges the model to learn invariant features of skin lesions, enabling accurate predictions despite variations in image characteristics. The visual representation of the dataset composition serves as a qualitative validation of its quality and diversity, aiding researchers. and clinicians with confidence in the model's ability to generalize to new cases. Through this meticulous approach to dataset curation and visualization, the study establishes a strong foundation for developing a deep learning model that can effectively classify skin lesions, ultimately improving diagnostic accuracy and patient outcomes in dermatology.

Table 1 Image Dispersal

Class Levels	Training	Testing
Malignant	949	248
Benign	1160	280
Total	2109	528

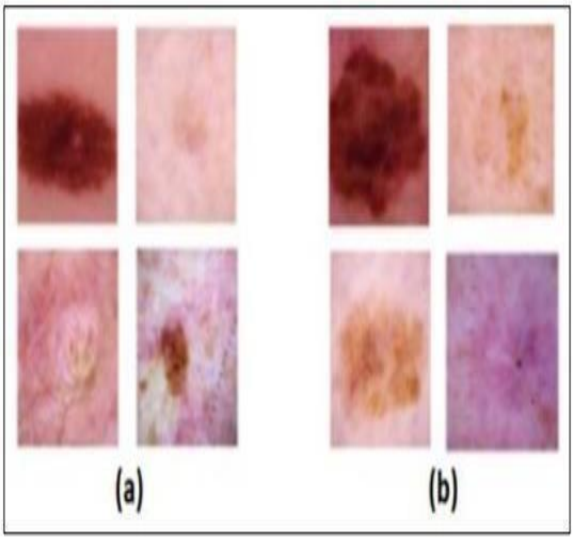

Figure 1 Class Levels images

3.2 Image Pre-Processing

Preprocessing is vital for improving the consistency of classification outcomes and optimizing feature extraction for all images in a dataset. This crucial step involves techniques like normalization, augmentation, and noise reduction to refine input data quality, ensuring the images are in optimal condition for analysis. Normalization scales pixel values to a standardized range, such as [0, 1], which helps reduce the impact of variations in pixel intensity across images. Augmentation techniques, as discussed earlier, are used to

Increase the diversity of the dataset and make the model more robust to variations in image characteristics. Noise reduction techniques, on the other hand, aim to remove unwanted artifacts or disturbances from the images, improving the clarity and quality of the data.

By standardizing the dataset through preprocessing, we can mitigate the variability and noise inherent in raw data, thereby improving the accuracy and reliability of the model's predictions. Standardization also ensures that the model is trained on a consistent and uniform dataset, which is essential for learning meaningful patterns and features. Additionally, preprocessing helps in reducing the computational complexity of the model by simplifying the input data and removing irrelevant information. This, in turn, leads to faster training times and more efficient use of computational resources.

In preparing the dataset for deep learning models, preprocessing plays a pivotal role, ensuring they are trained on top-quality data conducive to accurate and dependable classification results. Through preprocessing techniques, researchers and clinicians can optimize model performance, enhancing the classification accuracy of skin lesions and ultimately improving diagnostic precision and patient outcomes in dermatology.

Given the iterative training process of deep learning, where the model continuously adjusts its parameters to minimize errors, a substantial dataset becomes indispensable. A large and diverse dataset helps capture a broad range of variations and patterns, essential for the model to generalize effectively to unseen samples. This abundance of data acts as a defense against overfitting, where the model performs well on training data but struggles to generalize to new, unseen data.

When a model learns noise and random fluctuations in addition to the underlying patterns—which are unrelated to the job at hand overfitting takes place. The dataset needs to be large and representative of the kinds of real-world situations the model faces in order to handle this. Exposure to diverse examples enables the model to discern relevant patterns from noise, enhancing its ability to generalize.

Furthermore, techniques like cross-validation and regularization can be employed to ensure robust performance across different dataset subsets. Cross-validation involves dividing the dataset into multiple subsets and training the model on various combinations, aiding in assessing performance on unseen data and mitigating overfitting risk. Regularization entails

incorporating a penalty term into the loss function during training to prevent the
By utilizing a substantial and diverse dataset, alongside techniques to combat overfitting, researchers and clinicians can develop more robust, accurate, and generalizable deep learning models. These models can then be applied effectively to healthcare challenges, including skin lesion classification, resulting in improved diagnostic accuracy and patient care.

To summarize, preprocessing is a crucial step in the data pipeline, enhancing image quality and consistency to facilitate improved feature extraction. This process involves employing various techniques such as normalization, augmentation, and noise reduction, collectively preparing the dataset for training deep learning models. Normalization ensures pixel values are standardized, making the data more consistent and easier for the model to process. Augmentation techniques increase dataset diversity, exposing the model to a broader range of variations and patterns. Noise reduction methods remove unwanted artifacts from images, enhancing data clarity.

The importance of a substantial dataset in deep learning cannot be overstated, as it plays a critical role in mitigating overfitting and ensuring robust model performance with new, unseen data. A large, diverse dataset captures a wide range of variations and patterns, essential for effective model generalization. This data abundance acts as a buffer against overfitting, where the model learns not just patterns but also noise and fluctuations. Techniques like cross-validation and regularization address overfitting concerns. Cross-validation divides the dataset into subsets for varied model training, evaluating performance on unseen data. Regularization adds a penalty term during training, discouraging overly complex pattern learning.

Through meticulous preprocessing and the availability of a comprehensive dataset, we can develop a more reliable and effective deep learning model capable of generalizing well to various real-world applications. By standardizing the dataset and ensuring it is diverse and representative of encountered data, we can enhance the model's effectiveness. ability to accurately classify skin lesions and other medical conditions. This, in turn, leads to better diagnostic accuracy and patient outcomes in dermatology and other healthcare fields.

3.3 Visual Reshaping

Each image in the dataset undergoes a careful resizing process to standardize dimensions to 224 × 224 pixels. This resizing step is crucial, serving multiple purposes that collectively enhance the deep learning model's performance. Standardizing image size ensures consistent input format, streamlining subsequent data processing and model training stages. In deep learning applications, where convolutional neural network (CNN) architectures typically expect fixed-size input images, this standardization is particularly vital[34].

Standardizing image dimensions also reduces model computational complexity by ensuring all input images have the same number of pixels. This simplifies CNN layer operations, allowing for more efficient image processing. Additionally, resizing images to a uniform size preserves lesion aspect ratio, crucial for maintaining diagnostic relevance, as any distortion could impact lesion classification accuracy.

Resizing images to a standard size facilitates better comparison and analysis of CNN-extracted features. With all images represented in the same format, it becomes easier to identify patterns learned by the model. Uniform image size simplifies visualizing intermediate CNN representations, providing insights into image processing and decision-making. Further more, the resizing process helps in optimizing the use of memory and computational resources during model training and inference. Since all images are resized to a fixed size, the model can allocate memory more efficiently and process the images faster, leading to improved performance and reduced computational costs. Overall, the resizing step plays a crucial role in preparing the dataset for deep learning model training, ensuring that the images are in the best possible condition for subsequent analysis and classification.

Furthermore, adjusting the dimensions of images to 224 × 224 pixels significantly boosts the efficiency of the model. By employing smaller, consistently-sized images, the computational burden is lessened, enabling the model to handle data with greater speed and efficacy. This decrease in data volume results in expedited training and inference durations, thus hastening the overall processing pace. Quicker processing rates not only enhance model training but also facilitate its deployment in real-world scenarios, where rapid responses are imperative. Additionally, resizing images fosters enhancements in model performance.performance by

Improving the utilization of computational resources is facilitated by standardizing image size. This ensures more predictable and manageable memory requirements, allowing for the utilization of larger batch sizes during training. Larger batches can result in more stable gradient estimates and quicker convergence, leading to a more reliable and precise model.
Moreover, resizing images to 224 × 224 pixels often accompanies other preprocessing methods like normalization and augmentation, further enriching dataset quality and diversity. Normalization scales pixel values appropriately, reducing the risk of numerical issues during training. Augmentation, including rotation, flipping, and color adjustments, expands the dataset artificially, offering additional image variations for improved generalization to new data.
In essence, resizing images to 224 × 224 dimensions in the dataset is a pivotal preprocessing step that significantly boosts model efficiency and speeds up processing. This not only simplifies the input format for deep learning models but also enhances overall performance by optimizing computational resource utilization and facilitating other preprocessing techniques for improved data quality.

3.4 Data Augmentation

Augmented data holds immense significance in skin image classification, akin to its notable impact on pulmonary image classification. The realm of medical imaging presents unique challenges, particularly in accurately labeling skin images, requiring expert input from radiologists or dermatologists for dependable annotation. Due to the specialized knowledge needed, the availability of labeled medical images is often restricted, posing difficulties in developing robust deep learning models for precise diagnosis and classification.
In this regard, data augmentation emerges as a vital method for expanding and diversifying the training dataset. This process entails applying various transformations to existing images, like rotation, flipping, scaling, and color adjustments, to generate additional synthetic images. These augmented images represent diverse variations and conditions the model may encounter in real-world scenarios, thus enriching the dataset and offering a broader array of examples for model learning.
Through dataset augmentation, we can tackle the scarcity of labeled medical images, a common bottleneck in medical image analysis. Augmentation techniques effectively bolster

More data variety in a more extensive data set improves learning ability. Moreover, growth in the variability of the training data is not an indicator for more manual annotations at great expense in time. Now, more extensive and more diverse datasets will allow good generalization of noise and variability by those models, such that they reflect real-world changes not having been trained on new, unseen data.

In other words, these augmented data increase the diversity of the conditions in which the model is trained, hence increasing the model's stability due to their ability to generally pick features and patterns that are presented in different contexts. It then enables the model not to overfit new data, which is its characteristic of being too specialized in training data and, therefore performing poorly in new data. With a larger dataset to learn from, the model may better understand the underlying patterns, leading to better performance and higher reliability in the clinical setup.

In summary, augmented data is as essential in skin image classification as in pulmonary image classification. The particular issues in medical images, not to mention a perfect market for proper labeling, suggest the necessity of data augmentation, given that the value of the appropriate training set is stretched and improved. Not only does it compensate for the scantiness of images needed in the medical field, but it also boosts stability and reduces the level of overfitting due to increased generalization brought about by the introduced believable variance.

The data augmentation technique has applied the wide-array systematic method using the PictureDataGenerator function in the Keras library under the Python environment. The techniques described here apply to all types of alterations that lead to helping to create variability in the data and reflect different situations that come alive in real-world scenarios. The main transformations applied are scaling, rotation, shifting of width, shifting of height, zoom, horizontal flip, perturb in brightness, and shift of channels. Each augmentation is finely parameterized to thus make sense, in terms of keeping computation efficient and at the same time, not straying far from the original image data.

For example, normalizing the pixel value ranges from zero to one is on the basis for deep learning to converge. For 15-degree rotated images, this will aid in creating a little diversity in orientation in the process, making the model responsive to that. This shifted the 0.1 widths and height; therefore, we have

The 10% size of the images, in the horizontal and vertical shifting, will help the model to learn how to find objects if not located ideally in the center. The image is zoomed and the factors are maintained between 0.2 to 1.0; this will help the model view the enlarged and reduced versions of the image, and it will be able to look at the features at different scales much better.

There was also the horizontal flipping trick-p, which turned the images about the vertical axis, doubling the training samples and training the model to recognize objects in a left-right orientation. For changes in brightness, it brought the ability to represent the same image under another lighting condition. The model becomes robust in performance under almost any lighting condition. The shifting was done using a channel-shifting technique in close fill mode, where the color channels of the image were retained, indicating that only the original coordinate intensity was shifted into the color channels. The entire idea is to achieve a robust model against shifts in the distribution of colors in data.

All these are well-thought-out methods for augmentation and are combined to augment a robust and heterogeneous training data set, finally enhancing the generalization of our model. We map the model over various transformed images to learn essential features of the data. Such augmentation, making the data to train the dataset rich in information, will play a pivotal role in its development as an adaptive, applicable, and accurate deep-learning model for practical purposes in real life. applications.

Methods	Value
Scale_Transformation	Ranged from 0 to 1
Rotation_Range	15 degree
Width_Shift_Range	0.1
Height_Shift_Range	0.1
Zoom_Transformation	0.2
Horizontal_Flip	True
Vertical_Flip	True

Table 2 Reinforcement Method

3.5 Pre-configured Neural Network

3.5.1 NASNet Model

AutoML and NAS have emerged as prominent figures in the CNN domain, with NASNet, in particular, gaining attention. NASNet, a CNN trained on the expansive ImageNet dataset, is renowned for its adept feature extraction tailored for image recognition tasks. Illustrated in Figure 2, NASNet's architecture and optimization method are standardized. It offers two versions: NASNetMobile, for lightweight networks, and NASNetLarge, for more intricate architectures. NASNetMobile emphasizes resource efficiency and employs a search mechanism to find optimal convolutional layers or cells,[26] especially beneficial for smaller image datasets. Through convolution cells, NASNet enhances classification performance while minimizing computational costs. Moreover, it accommodates images of various sizes by constructing normal and reduction cells, ensuring adaptability across different image dimensions. Diverse cell configurations have been developed to optimize NASNet's architecture for efficient CNN designs with minimal computational burden. While NASNet's overall structure is predetermined, individual cells or building blocks are adjustable parameters during the reinforcement learning search process. For instance, parameters like normal cells maintain feature map size, while reduction cells halve feature map size in both dimensions. The controller RNN exclusively explores cell structures. Table 3 outlines the essential parameters. used during the training of the NASNet Mobile model. Both Adam and Nadam optimizers were employed, with categorical cross-entropy serving as the loss

Methods	Value
Type of Transfer	From Scratch Transfer Knowledge
Train Layers	All
Optimizers	Adam, Nadam
Learning Rate	True
Activation Function	ReLu and Sigmoid
Loss Function	Categorical Cross-entropy
Batch Size	32
Epoch	30

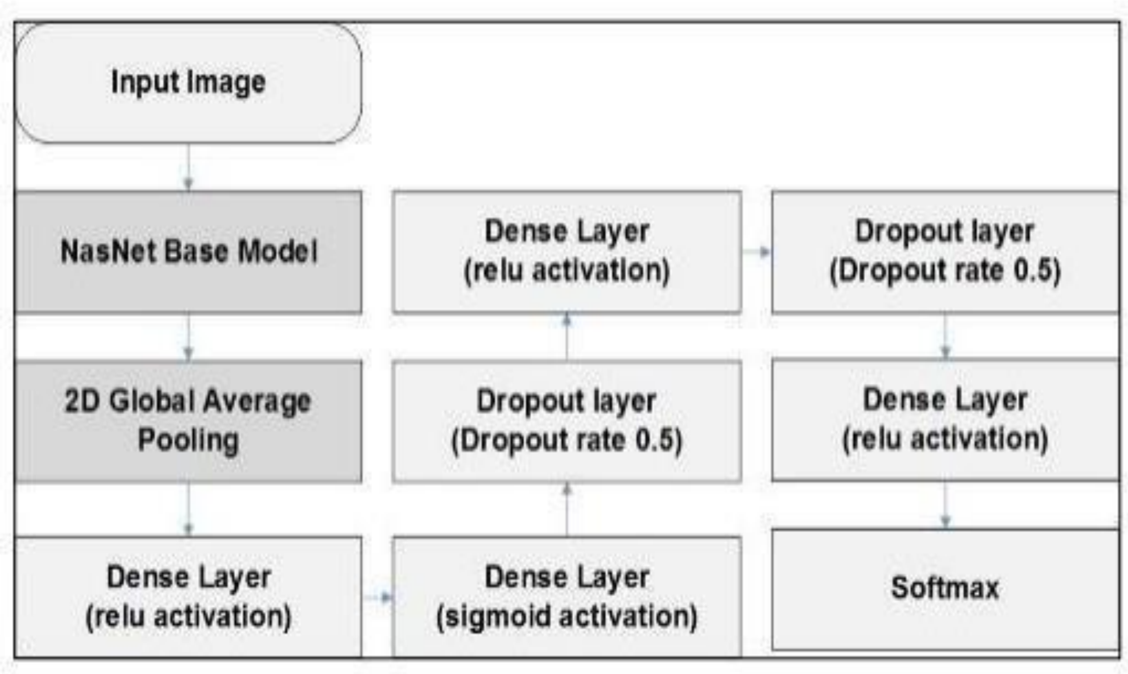

Figure 2 Optimization of NASNet Model

Figure 2 illustrates the intricate optimization process of the NASNet Mobile model, meticulously crafted to improve performance and efficiency in image recognition tasks. Following the foundational architecture of the NASNet base model, the process initiates with the utilization of a 2D Global Average Pooling (GAP) layer. This layer plays a crucial role by condensing each feature map into a single value, effectively reducing spatial dimensions and summarizing global context. This reduction is pivotal in transforming high-dimensional data into a more manageable form, significantly lessening computational load while retaining essential features for accurate image recognition.

The model then employs a series of advanced convolutional operations, fine-tuned through an extensive search algorithm to identify optimal architectural configurations. These configurations aim to maximize model accuracy while minimizing computational resources. Convolutional layers are adept at extracting intricate patterns and features from input images, progressively refining data through multiple layers of abstraction. Additionally, the NASNet Mobile model integrates various optimization techniques like batch normalization and dropout to enhance model generalizability and robustness[34][33][26].

Batch normalization standardizes inputs to each layer, thereby expediting training and

Increase network stability. On the other hand, dropout is used to regulate Utilized to avert overfitting; dropout randomly omits some neurons in the process of training; hence, the model cannot over-rely on one feature. These optimization methods are well-equipped to make a model effective and accurate for Image RE Identification, which is apt for low-resource environments like mobile devices. `, The NASNet Mobile model is the latest deep learning and image recognition breakthrough technology, which strikes a balance between performance and efficiency.

After the GAP layer is the dense layer, to which it is meticulously appended so that it is connected directly to the output of the GAP layer. Connected and feature-transforming, the dense layer prepares the data so that in the later stages of model processing, it poses no difficulty. The activation layers include various acts, such as Sigmoid, ReLU, and Tanh; therefore, it provides an opportunity to introduce non-linearities in the network at strategic positions. These non-linearities make the model expressive enough to capture intricate data patterns in the final run, leading to the overall performance and accuracy. A careful choice and implementation of these activation functions ensure that, in the end, the network is enabled to handle a wide range of input data by enhancing the

Generalization of the NASNet Mobile model under several tasks in the image recognition field.

Having chosen the ReLU function as it has characteristics to alleviate the vanishing gradient and encourage activation sparsity since it has been confirmed in practice to capture well linear relationships, the embedded activation function in the second dense layer is the sigmoid activation function. Since it squashes its output into a minimal range of 0 to 1, it makes it very useful when outputs have to be interpreted as probabilities, like in the case of binary classification.

The dropout layer uses a rate of 5% for parameter fine-tuning to achieve robustness without overfitting. The dropout layer specifies a random set of neurons to zero for each training cycle. This, therefore, introduces a way of regularization whereby a lot of the model's complexity will be lessened. Using this dropout mechanism naturally imposes upon the network the maintenance of redundant data representation. Redundancy at this level is significant for increasing the model's generalization capability so that it doesn't overfit the data it's trained on but performs better on unseen data. The dropout layer is deliberately introduced to set an intended balancing point between generalization and model complexity, hence ensuring that the achieved performance of the NASNet Mobile model will be sustained to the best of its ability in the task at hand.performance.

The other dense layers are then inserted between these slowly embedded model architectures, interleaved further with more dropout layers. These layers work with courtesy in processing and purifying the characteristics derived from the input data in such a sensitive manner through the application of dropouts in quick successions. Dense and dropout layers are placed so majestically that they serve the very purpose of feature extraction and keeping it robust through model development. This way, serial ordering ensures the complex view of input data built up bit by bit, and the network can optimally learn how to classify and recognize an image at present. The softmax activation function is purposely used so that a precise final classification can be obtained, therefore completing the whole optimization process. The function maps the concatenation of the logits produced by the last dense layer into a target-class probability distribution in such a way that the summation of distribution values will be one. This last property is fundamental from the classification perspective: an obvious interpretable value of predictions for every input image that makes the model perform very lovely with the confidence estimate in classes. This fully connected layer complements these dense layers with the addition of dropout layers and integrative softmax activation functions, allowing the model for the NASNet Mobile to perform at a very high level of accuracy and robustness, effectively solving the challenge of image recognition that is highly variant across the environment.

In this light, it can be concluded that the optimization process outlined in detail for the model NASNet Mobile, as shown in Figure 2, outlines the clear and relatively complex strategy used to provide the highest level of performance in recognizing visual images. This is done at a 2D global average pooling (GAP) layer on the feature maps, which it means the spatial dimensions were compressed into single values. In so doing, it encapsulates global context and serves as a way of reducing computation complexity. After this GAP layer, sequences of dense layers are given and each one interfaces directly with the previous layer's output. Such dense layers come with strategic activation functions like ReLU (Rectified Linear Unit) and Sigmoid, which bring essential nonlinearities into the network. Such nonlinearities contribute to the improved expressiveness of the model and the ability to capture intricate patterns in the data; therefore, they allow a network structure that can differentiate complex relationships and dependencies between features. Notably, numerous Dropout layers are systematically embedded in the Dense layers for the sake of generic learning and avoiding overfitting. In each epoch of the training process, all the dropout layers are passed, while a random set of neurons is turned off. This way, a model developed using dropout simplifies to some extent and is encouraged to create redundant representations in the network. Thereby, the model will

It will then perform better on unseen data and be more stable. Thus, care is taken so that the overall stacking of such dense and dropout layers will be a strategy on the best features yet still stably trained across settings for diverse image recognition tasks.

Eventually, the optimization pathway ended with the implementation of a softmax activation function, which is quite essential in ending the classification objectives in the model. Softmax provides a way to convert these logits—the outputs of the last dense layer— to some probability over the target class with the property that the sum of the probabilities is 1. It is a technique used in classification problems, whereby for each input image, the resultant output must be a unique interpretable prediction. In other words, the activation of the softmax assigns a confidence level to each class, reflecting that the model makes the best classification which is reliable and correct.

Other inferences are drawn from the fact that the models of structures of NASNet Mobile contain strategic activation functions covered with the GAP layers, dense layers, and many dropout features combined with finesse implemented at once with optimization. It has to be underlined that approaches finely tuned can deliver good and reliably classified cases that are well representative of model effectiveness in the cases of recognition of different images. This detailed model optimization and design refinement of the NASNet Mobile model illustrates a principled approach to advanced deep learning, focusing strongly on how effective the amalgamation of sophisticated techniques may be in achieving exceptional performance.

3.6 Performance Evaluation

Tables 4 and 5 meticulously detail the confusion matrices (CM) corresponding to the application of both NASNet Mobile and NASNet Large models, utilized alongside the Adam optimizer. These tables offer a comprehensive breakdown of performance metrics, showcasing the models' accuracy in classifying input data across diverse categories. By presenting counts for true positive, false positive, true negative, and false negative outcomes, these matrices provide a thorough analysis of classification accuracy and the models' ability to differentiate between various classes.

The inclusion of the Adam optimizer, renowned for its efficiency and adaptive learning rate capabilities, further elevates the performance of these NASNet architectures, ensuring robust training and optimal convergence. The adaptive learning rate mechanisms of the Adam optimizer enable it to dynamically adjust the learning rate for each parameter, taking into

Also, it maintained gradient magnitudes and the exponentially decaying average of past gradients. This way, it adapted the optimizer, which navigated hard, high-dimensional parameter spaces, leading to faster convergence and better model performance.
Moreover, the gateway connects further into integrating the Adam optimization techniques to the NASNet Mobile and NASNet Large models. This is purposive in nature so that the models can have the ability to garner maximum optimization towards better generalization and move towards eliciting emergence as the most reliable and effective recognition systems meant for images.

In other words, the detailed analysis presented in Tables 4 and 5, through the confusion matrices between the models NASNet Mobile and NASNet Large, with the Adam optimizer, supports the robustness and performance of these models in the correct classification of the input data. These wide performance measurements present summaries for the models about true positives, false positives, true negatives, and false negatives and offer an extensive view of the classification accuracy of the model over diverse classes.

In addition, Adam optimization upgrades this with more use on effectiveness and adaptive learning rate properties. This optimizer guarantees ultimately that the model will converge quickly with better performances in highly complex and high-dimensional parameter space, dynamically changing the learning rates for every change in the parameter, guided by the gradient magnitudes and the earlier gradients. This testifies to such a degree of seriousness with which models are being fine-tuned continuously and evaluated for moving a step further in deep learning, which has been applied to image recognition. It is rugged in the sense that the very capabilities of the NASNet Mobile and NASNet Large models are of critical value in categorizing strictly categorized input data in practical circumstances. The performance of these models was ensured effective during the implementation process. The use of the Adam optimizer was proof for development in the future in the area of deep learning.field.

		Actually Positive	Actually Negative
		1: Malignant	0: Benign
Predicted Positive	1: Malignant	213	35
Predicted Negative	0: Benign	42	238

Table 5 Confusion Matrix for NASNet Large

		Actually Positive	Actually Negative
		1: Malignant	0: Benign
Predicted Positive	1: Malignant	198	50
Predicted Negative	0: Benign	37	243

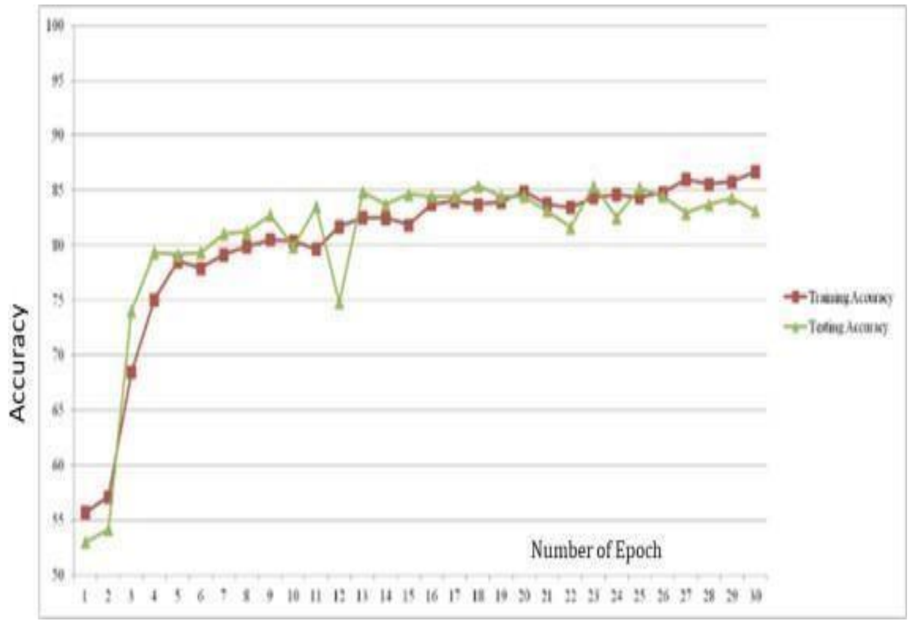

Figure 3: Relationship Between Epochs and Accuracy in NASNet Mobile Pre-traning

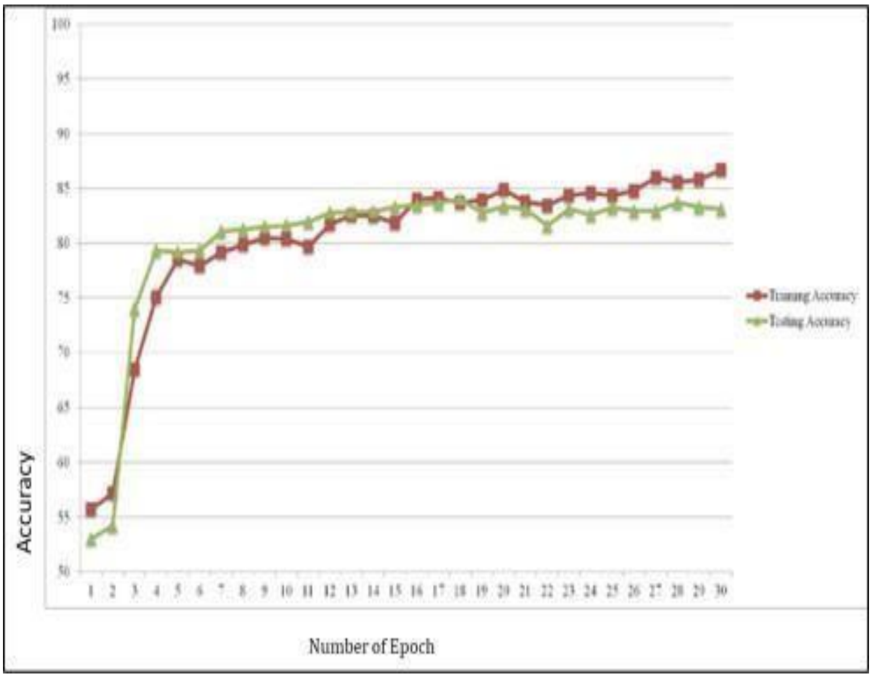

Figure 4: Relationship Between Training Epochs and Model Accuracy in NASNet Large

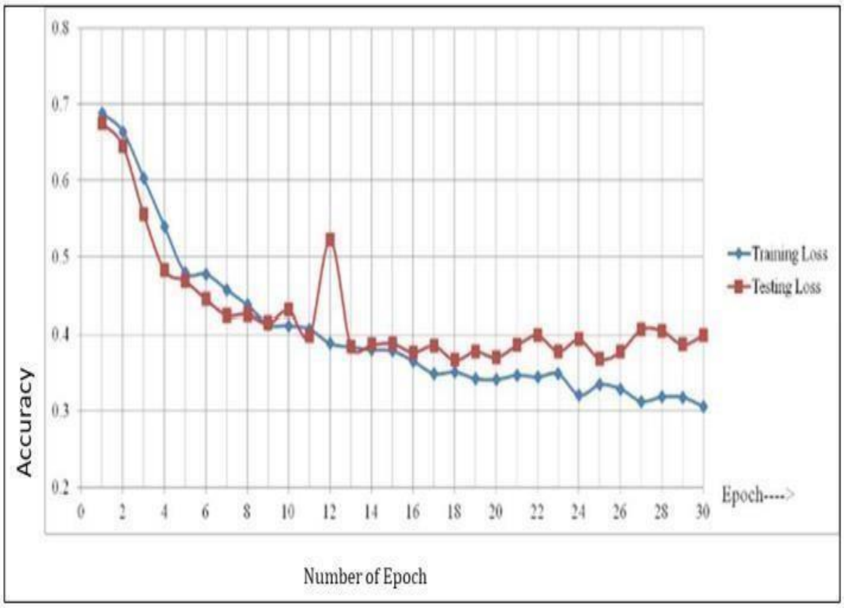

Figure 5 Relationship Between Training Epochs and Loss in NASNet Mobile

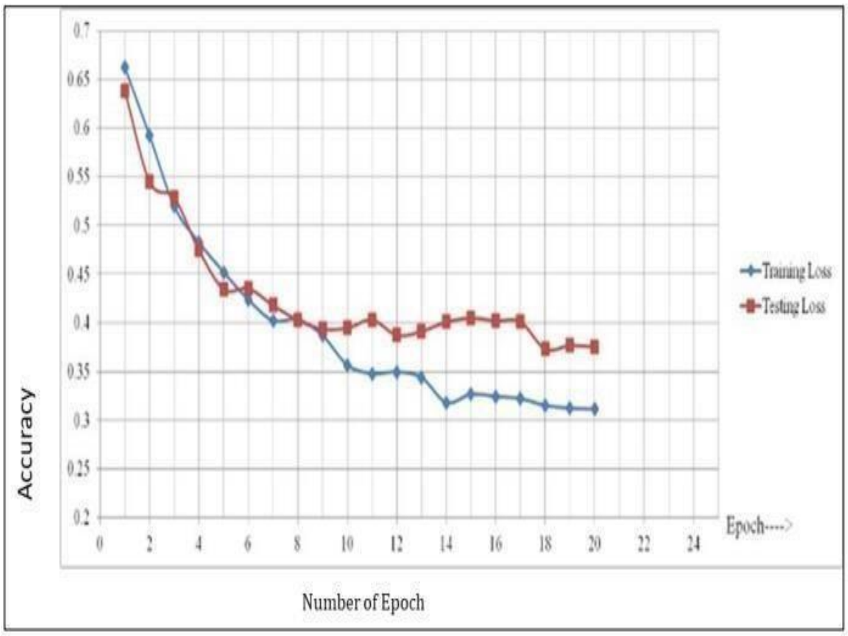

Figure 6 Relationship Between Training Epochs and Loss in NASNet Large

Figure 3 and Figure 4 meticulously depict the intricate relationship between Epoch and Accuracy for the NASNet Mobile and NASNet Large models, respectively. These figures provide a detailed visual representation of how accuracy evolves with each training epoch, allowing for a comprehensive analysis of the learning dynamics and performance improvements of each model over time. By observing these figures, researchers and practitioners can gain insights into the models' learning curves, identifying patterns of convergence, plateaus, or fluctuations in accuracy that may indicate areas for further optimization or improvement.

Similarly, Figure 5 and Figure 6 demonstrate the relationship between Epoch and Loss for the NASNet Mobile and NASNet Large models, respectively. These figures depict how the loss metric, a crucial indicator of model performance, evolves during training, revealing the models' convergence patterns and the effectiveness of the training regimen. A decrease in loss signifies successful error minimization and enhancement of predictive capability, while spikes or irregularities may indicate issues like overfitting or insufficient training data.

The detailed visualization of these associations through figures offers valuable insights into the training dynamics and performance characteristics of the NASNet Mobile and NASNet Large models. This visual representation is pivotal for comprehending the models' behavior and making informed decisions regarding model optimization, hyperparameter tuning, and training strategies. The thorough examination enabled by these figures contributes to the advancement of deep learning research, emphasizing the importance of visualizing performance metrics for model evaluation and enhancement.

Moreover, Figure 7 displays the ROC (Receiver Operating Characteristic) outcomes of the proposed NASNet models meticulously trained with the Adam optimizer. This figure provides an in-depth analysis of the models' ability to differentiate between various classes, illustrating the balance between sensitivity and specificity. The ROC curve plots the true positive rate against the false positive rate at different threshold settings, offering a comprehensive overview of the models' classification performance across varying decision thresholds.

Significantly, these findings underscore the superior performance of the optimized NASNet models compared to alternative models, evident from their robust ROC curves and high AUC (Area Under the Curve) values. A higher AUC value indicates better discrimination between positive and negative classes, with a value of 1 representing a flawless classifier. The exceptional performance of the NASNet models in ROC analysis

This further underlies their effectiveness in any classification task, attesting to their applicability at best in real-world situations where the proper classification is a must.
The models are then subjected to extensive training through optimization with the help of the Adam optimizer such that peak performance can be guaranteed, resulting in maximum and effective convergence for training the parameters of the models. The advanced optimization techniques are inherently adapted to the native structure of the NASNet models for developing a robust and reliable classification framework that works most optimally in the complex image recognition problem. From the obtained results in Figure 7, it can be concluded that the NASNet models, while being developed into the techniques and methodologies of deep learning for image recognition, have sleek performance and are thereby versatile for applications demanding fast and accurate classification.

Also obtained are the two values of AUC, 0.92 and 0.87, for the classes, two examples of which are given in Figures 9 and 10. These figures record very high potential for the posted models to provide a high discriminative power since the AUC values close to one describe excellent classification performance. This AUC metric is quite essential for a binary classification problem, as it gives a summary concerning the ability of the model to differentiate between the positive and negative instances. A significant value for AUC implies that the model is good enough to rank positive instances in a higher position than negative ones; hence, it can classify unseen data with relatively high accuracy.

All visual and general quantitative analyses in the sections above bear collective testimony to the powerful potential of NASNet, fine-tuned by using the Adam optimizer not only to yield state-of-the-art accuracy performance but also to be ultimately stable and rock-solid over most of the evaluation metrics.
High AUC scores remind us that the model is susceptible to changes within classes and specific ways, which will be helpful to obtain a high level of classification accuracy in its application. This is the first result that comforts: NASNet models, which can help handle complex image recognition tasks and pave the way for great potential for application in real-world scenarios. It is important to note that the results in Figures 9 and 10 point to the overall importance of the NASNet models developed in furthering deep learning and image recognition, as the models presented higher AUC values when compared to the others. In turn, this implied a higher discriminatory strength. these models

establish a new standard for accuracy and performance in classification tasks, highlighting their suitability for various applications demanding accurate and dependable classification. image classification.

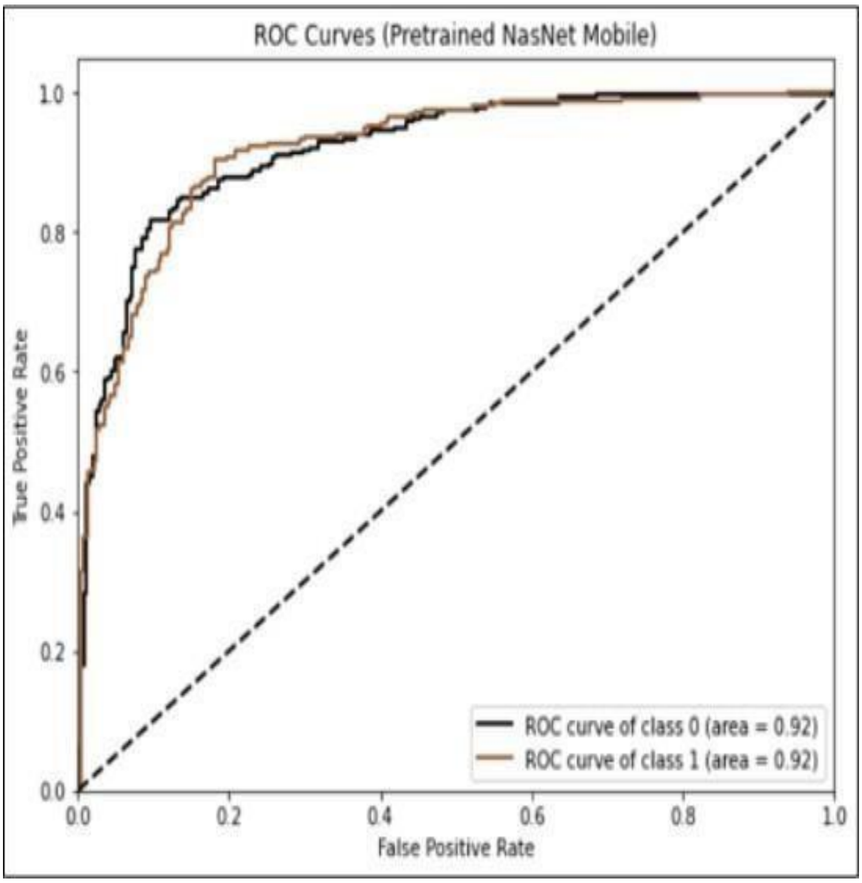

Figure 7 Evaluating ROC Curve Performance for NASNet Mobile using Adam Optimizer

Based on the comprehensive findings meticulously presented in Table 6, it becomes evidently clear that the proposed optimized NASNet model exhibits exceptionally favorable levels of accuracy and sensitivity. These performance metrics significantly surpass those observed in various other deep learning models that have been previously employed and evaluated in different research studies. This comparative analysis highlights the superior capabilities of the optimized NASNet model[16], demonstrating its efficacy and robustness in handling complex classification tasks with greater precision and reliability. The data underscores the model's ability to achieve higher accuracy rates and improved sensitivity, which are critical for effective image recognition and classification, thereby establishing the optimized NASNet model as a leading contender in the field of deep learning applications.

Table 6 Evaluation of Proposed Method Relative to Alternative Models

Model	Sensitivity	Specificity	Precision	Accuracy
ResNet [33]	50.71%	74.10%	67.76%	75.31%
VGG 19 [33]	50%	71.89%	65.22%	73.11%
VGG Net [34]	78.66%	-	79.74%	81.33%
Shifted MobileNet V2 [35]	65.9%	95.2%	71.4%	81.9%
Shifted GoogLeNet [35]	58.1%	94.7%	68.5%	80.50%
CNN [36]	-	-	-	78%
ResNet-50 [37]	85%	-	86%	84.87%
VGG 16 [37]	81%	-	82%	81.27%
CNN [37]	76%	-	14%	76.33%
MobileNet [38]	-	-	-	77.31%
DenseNet [38]	-	-	-	79.39%
ResNet 50 [38]	-	-	-	81.05%
ResNet50 + DenseNet [38]	78.31%	82.42%	-	81.64%
Proposed NASNet (Ours Model)	84.23%	87.25%	86.19%	86.73%

CHAPTER 4

CONCLUSION

This offers a new perspective for the classification of skin cancer as opposed to past methods, using NASNet to compare extensive methodologies. Most importantly, this use of the recently enhanced transfer learning methods in categorization with skin cancer pictures offers the potential further to improve the classification accuracy and precision regarding skin cancer. Moreover, the overall results indicate that the architecture added NASNet, a factor that gives a massive uplift in performance over the core DCNN model when classifying the skin images in a dataset. [20][24][35] In general, the architecture added NASNet was a neural architecture search framework that optimized the structures of deep learning models in a task to classify skin cancer. This approach allows for finding very effective neural architectures that are already well-tailored to different complexities of the skin cancer image data. In principle, it will harness pre-trained weights and architectures learned from large-scale datasets, such as ImageNet, using transfer learning. Pre-training increases the inductive capacity of the model towards generalization over the skin cancer dataset by inducting generic features useful for other classification tasks.

Specifically, the present study undertook and elaborated on the built model's performance superiority over traditional DCNN models using analyzing and comparing with the built model on the NASNet [19]. This model does better at classification results based on precision and accuracy, providing objective measures of the classification efficiency used in handling complexities of skin cancer image classification. Transfer learning through the use of NASNet made it possible to achieve excellent classification performance due to its precision performance, which far exceeded that of the DCNN model, albeit by using a considerably smaller dataset. Notably, the need for a pre-trained model to fine-tune for a more specific task naturally arises in domains where data is scarce. This work concludes a leap forward in the overall classification of skin cancer with the proposed new approach, in which all previous studies are outperformed when using the combination of NASNet and transfer learning [20][24][35].

The use of such advanced models offers great promise of enabling efficient.

This, therefore, makes the application of NASNet, more especially transfer learning, very practical and reliable in a computer-aided diagnostic, especially in problem-solving where data scarcity comes as a challenge in cases of skin images. The following become highly important in the medical scenario since the accuracy and the on-time prognosis may highly determine the future course of health. Our study revealed how the potentials of such combination techniques could bring to light the transformation that diagnosis of skin cancer was about to pass through by utilizing strengths that reside in NASNet and transfer learning themselves. Future research needs to broaden the base for applied purposes in the field of medical image analysis to open paths that afford generalization to new and unseen data, even though with very few labeled samples, to successfully achieve the highest accuracy and efficiency in diagnoses made in clinical settings. Moreover, advanced techniques save time for physicians and then lessen the workload on physicians by giving them reliable tools so physicians can focus more on taking care and making decisions for the treatment of patients.[35, 24, 20]

Aside from deep learning, jointly incorporating transfer learning with NASNet can be fitted into other diagnoses with the hope of presenting skin cancer—that is, the gain in profound learning dominance over medical imaging. As these processes grow, so, although the background, the use of transfer methods in the foreground accrues, increasing diagnostic accuracy for an ever-growing number of medical conditions.

So, they can be scalable and adaptive to the already-in-place infrastructural frame of health care and ensure a smooth and effective way to take the diagnostic ability in a further elevating stage. In general, this study proves the NASNet, together with transfer learning, is a working tool for significant problems in the scope of diagnostic with skin cancer, underlining the more general role of medical analysis in images for advanced and more patient care. In this respect, fine-tuning is a severe process toward precision in skin image classification by NASNet transfer learning, as observed in this work. However, one must think about the results that could occur when choosing the wrong transfer learning network, which could result in lousy transfer effects, hence reducing accuracy and increasing training time.

Thus, a good scope exists for further inquiry into optimization efforts toward the network selection strategy for any purpose related to skin imaging tasks. The scope of work is quite promising and tries to further improve the state of the art of computer-aided diagnostics towards transfer learning techniques for practical improvements in the accuracy and the efficiency of the skin cancer classification systems,[35][24[20].

In simple words, fine-tuning is a process of retraining the already pre-trained parameters of neural networks on a new dataset. In the context of the problem of skin cancer classification, curation of the NASNet model allows the model to tune learned features so that, through skin images, they match characteristics found in a better way, thereby attractive performance moving upwards. However, those hopefully vary with the choice of the pre-trained network and how similar the original and new tasks are for skin cancer classification. In such a scenario, one might come under negative transfer, reducing the model performance in transfer learning rather than increase it. This embeds the importance of the careful selection of a pre-trained network aligned with the characteristics of skin images.

Within this future research line, considerations will be made on ways to work out improved strategies for the selection of pre-trained networks during tasks in the field of skin imaging. This can hold across different architectures, training strategies, or characteristics of datasets that might lead to the identification of the most appropriate networks for which transfer learning will apply. This should be feasible with further research to enhance the design of new methodologies for adapting pre-trained networks to new tasks. Therefore, fine-tuning can be effected to overcome the challenges and achieve good performance with minimum risk of negative transfer. These advanced methodologies are expected to release complete transfer learning that will lead to the advanced classification of skin cancer, leading to more accurate and effective autonomous computer-aided diagnostic tools in dermatology.

REFERENCES

[1] Factors, R. Basal and Squamous Cell Skin Cancer Causes, Risk Factors, and Prevention. 2019. Available online: https://www.cancer.org/content/dam/CRC/PDF/Public/8819.00.pdf (accessed on 17 January 2023).

[2] Gandhi, S.A.; Kampp, J. Skin cancer epidemiology, detection, and management. Med Clin. 2015, 99, 1323–1335.

[3] Harrison, S.C.; Bergfeld,W.F. Ultraviolet light and skin cancer in athletes. Sport. Health 2009, 1, 335–340

[4] Skin Cancer. Available online: https://www.aad.org/media/stats-skin-cancer (accessed on 22 May 2022).

[5] Incidence estimate of nonmelanoma skin cancer (keratinocyte carcinomas) in the US population, 2012. JAMA Dermatol. 2015, 151, 1081–1086.

[6] Whiteman, D.C.; Green, A.C.; Olsen, C.M. The growing burden of invasive melanoma: Projections of incidence rates and numbers of new cases in six susceptible populations through 2031. J. Investig. Dermatol. 2016, 136, 1161– 1171.

[7] Xie, F.; Fan, H.; Li, Y.; Jiang, Z.; Meng, R.; Bovik, A. Melanoma classification on dermoscopy images using a neural network ensemble model. IEEE Trans. Med. Imaging 2016, 36, 849–858.

[8] Dalila, F.; Zohra, A.; Reda, K.; Hocine, C. Segmentation and classification of melanoma and benign skin lesions. Optik 2017, 140, 749–761.

[9] Cancer Stat Facts: Melanoma of the Skin. Available online: https://seer.cancer.gov/statfacts/html/melan.html (accessed on 22 May 2022).

[10] Melanoma: Statistics. Available online: https://www.cancer.net/cancertypes/melanoma/statistics (accessed on 22 May 2022).

[11] Bomm, L.; Benez, M.D.V.; Maceira, J.M.P.; Succi, I.C.B.; Scotelaro, M.d.F.G. Biopsy guided by dermoscopy in cutaneous pigmented lesion-case report. An. Bras. Dermatol. 2013, 88, 125–127.

[12] Kato, J.; Horimoto, K.; Sato, S.; Minowa, T.; Uhara, H. Dermoscopy of melanoma and non-melanoma skin cancers. Front. Med. 2019, 6, 180.

[13] Ibrahim, H.; El-Taieb, M.; Ahmed, A.; Hamada, R.; Nada, E. Dermoscopy versus skin biopsy in diagnosis of suspicious skin lesions. Al-Azhar Assiut Med. J. 2017, 15, 203.

[14] Rahman, S. M., Ibtisum, S., Bazgir, E., & Barai, T. (2023). The Significance of Machine Learning in Clinical Disease Diagnosis: A Review. arXiv preprint arXiv:2310.16978.

[15] Bazgir, E., Haque, E., Sharif, N. B., & Ahmed, M. F. (2023). Security aspects in IoT based cloud computing. World Journal of Advanced Research and Reviews, 20(3), 540-551.

[16] Ibtisum, S., Rahman, S. A., & Hossain, S. S. (2023). Comparative analysis of MapReduce and Apache Tez Performance in Multinode clusters with data compression. World Journal of Advanced Research and Reviews, 20(3), 519-526.

[17] Selim Molla, Ehsan Bazgir, S M Mustaquim, Iqtiar Md Siddique and Anamika Ahmed Siddique, “Uncovering COVID -19 conversations: Twitter insights and trends”, World

Journal of Advanced Research and Reviews, 2024, 21(01), 836 –842.

[18] Mondal, M. R. H., Bharati, S., Podder, P., & Podder, P. (2020). Data analytics for novel coronavirus disease. informatics in medicine unlocked, 20, 100374.

[19] Parvez, A. S., & Sarker, B. (2022). Role of IoT and Cloud Computing in Digital Healthcare. International Journal of Advanced Research in Computer and Communication Engineering, 11(4).

[20] Ahmmed, S., Podder, P., Mondal, M.R.H., Rahman, S.A., Kannan, S., Hasan, M.J., Rohan, A. and Prosvirin, A.E., 2023. Enhancing Brain Tumor Classification with Transfer Learning across Multiple Classes: An In-Depth Analysis. BioMedInformatics, 3(4), pp.1124-1144.

[21] Bipasha Sarker, Numair Bin Sharif, Mohammad Atikur Rahman, A.H.M Shahariar Parvez, "AI, IoMT and Blockchain in Healthcare", Journal of Trends in Computer Science and Smart Technology, Vol. 5, Issue:1, pp. 30 - 50, 2023.

[22] Alam, F. B., Podder, P., & Mondal, M. R. H. (2023). RVCNet: A hybrid deep neural network framework for the diagnosis of lung diseases. Plos one, 18(12), e0293125

[23] Rahman, S. M., Ibtisum, S., Podder, P., & Hossain, S. M. (2023). Progression and Challenges of IoT in Healthcare: A Short Review. arXiv preprint arXiv:2311.12869.

[24] Podder, P., Bharati, S., Rahman, M. A., & Kose, U. (2021). Transfer learning for classification of brain tumor. In Deep learning for biomedical applications (pp. 315-328). CRC Press.

[25] E. Nasr-Esfahani, S. Samavi, N. Karimi, S.M.R. Soroushmehr, M.H. Jafari, K.Ward, K. Najarian, Melanoma detection by analysis of clinical images usingconvolutional neural network, in: 2016 38th Annual International Conferenceof the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2016,pp. 1373–1376.

[26] S. Demyanov, R. Chakravorty, M. Abedini, A. Halpern, R. Garnavi,Classification of dermoscopy patterns using deep convolutional neuralnetworks, in: 2016 IEEE 13th International Symposium on BiomedicalImaging (ISBI), IEEE, 2016, pp. 364 – 368.

[27] A. Esteva, B. Kuprel, R.A. Novoa, J. Ko, S.M. Swetter, H.M. Blau, S. Thrun,Dermatologist-level classification of skin cancer with deep neural networks,Nature 542 (7639) (2017) 115.

[28] B. Walker, J. Rehg, A. Kalra, R. Winters, P. Drews, J. Dascalu, E. David, A.Dascalu, Dermoscopy diagnosis of cancerous lesions utilizing dual deeplearning algorithms via visual and audio (sonification) outputs: Laboratoryand prospective observational studies, EBioMedicine 40 (2019) 176–183.

[29] S. Ioffe, C. Szegedy, Batch normalization: Accelerating deep network trainingby reducing internal covariate shift, arXiv preprint arXiv:1502.03167

[30] S. Mishra, H. Imaizumi, T. Yamasaki, Interpreting fine-grained dermatological classification by deep learning, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2019.

[31] https://www.kaggle.com/code/fanconic/cnn-for-skin-cancer-detection/notebook [Dataset]

[32] Mijwil, M.M. Skin cancer disease images classification using deep learning solutions. Multimed Tools Appl 80, 26255 –26271 (2021). https://doi.org/10.1007/s11042-021-10952-7

[33] Thurnhofer-Hemsi, E. López-Rubio, E. Domínguez and D. A. Elizondo, "Skin Lesion Classification by Ensembles of Deep Convolutional Networks and Regularly Spaced Shifting," in IEEE Access, vol. 9, pp. 112193-112205, 2021, doi: 10.1109/ACCESS.2021.3103410.

[34] Nugroho, A. A., Slamet, I. & Sugiyanto,. Skins cancer identification system of HAMl0000 skin cancer dataset using convolutional neural network. AIP Conf. Proc. 2202(1), 020039 (2019).

[35] Mehra, A., Bhati, A., Kumar, A., Malhotra, R. (2021). Skin Cancer Classification Through Transfer Learning Using ResNet-50. In: Hassanien, A.E., Bhattacharyya, S., Chakrabati, S., Bhattacharya, A., Dutta, S. (eds) Emerging Technologies in Data Mining and Information Security. Advances in Intelligent Systems and Computing, vol 1300. Springer, Singapore. https://doi.org/10.1007/978-981-33-4367-2

[36] Ismail, M.A., Hameed, N., Clos, J. (2021). Deep Learning-Based Algorithm for Skin Cancer Classification. In: Kaiser, M.S., Bandyopadhyay, A., Mahmud, M., Ray, K. (eds) Proceedings of International Conference on Trends in Computational and Cognitive Engineering. Advances in Intelligent Systems and Computing, vol 1309. Springer, Singapore. https://doi.org/10.1007/978-981-33-4673-4_58

[37] Podder, Prajoy, Sanchita Rani Das, M. Rubaiyat Hossain Mondal, Subrato Bharati, Azra Maliha, Md Junayed Hasan, and Farzin Piltan. "Lddnet: a deep learning framework for the diagnosis of infectious lung diseases." Sensors 23, no. 1 (2023): 480

[38] Mondal, M. Rubaiyat Hossain, Subrato Bharati, Prajoy Podder, and Joarder Kamruzzaman. "Deep Learning and Federated Learning for Screening COVID-19: A Review." BioMedInformatics 3, no. 3 (2023): 691-713.

[39] Rubaiyat Hossain Mondal, M., Subrato Bharati, and Prajoy Podder. "Diagnosis of COVID-19 Using Machine Learning and Deep Learning: A review." arXiv e-prints (2021): arXiv-2110.

[40] Mondal, M. Rubaiyat Hossain, Subrato Bharati, and Prajoy Podder. "CO-IRv2: Optimized InceptionResNetV2 for COVID-19 detection from chest CT images." PloS one 16, no. 10 (2021): e025917