IMAGES-BASED SKIN DISEASE RECOGNITION USING A DEEP LEARNING APPROACH

BY

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "**Images-Based Skin Disease Recognition Using a Deep Learning Approach**", submitted by **Md. Sazzadur Rahman Bhuiyan** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **15th July,2024**.

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I ~~We~~ hereby declare that this project has been done by me under the supervision of **Narayan Ranjan Chakraborty, Associate Professor and Associate Head, Department of CSE Daffodil International University**. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Skin illnesses are common and varied, resulting from a range of causes including viral agents, allergies, bacterial infestations, and fungal infections. Even if advances in medical technology, especially in optics and photonics, have made it possible to detect skin diseases more quickly and accurately, the related expenses continue to be a barrier. To meet this difficulty, image processing methods show up as an affordable way to test for skin issues early on. This study tackles the urgent need for easily available and effective skin disease diagnosis, especially in light of the high incidence of these problems in places like Saudi Arabia where dry weather increases the risk of dermatological illnesses. Our study presents a cost-effective and timely technique for the detection of skin disorders based on image processing. The suggested approach entails taking digital pictures of the afflicted skin regions, which are analyzed to identify the precise illness kind. This method offers a quick and effective way to classify while also streamlining and expediting the diagnostic procedure. Our work highlights the importance of feature extraction in the categorization of skin diseases, as computer vision methods are used to improve detection accuracy. Our method, which uses these technologies, advances the field of disease of the skin investigation, and provides a useful resource for everyone looking for an accessible aesthetic screening as well as medical experts.

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CHAPTER 1

INTRODUCTION

1.1 introduction

Skin conditions are more prevalent than other illnesses. Skin conditions may be brought on by microbes, viruses, allergies, or fungi, among other things. Skin diseases may alter the skin's color or texture. Skin conditions are often contagious, long-lasting, and sometimes lead to skin cancer. Consequently, to stop the formation and spread of skin disorders, early diagnosis is essential. A skin illness requires more time for diagnosis and treatment, as well as more financial and medical expenses for the sufferer. The majority of everyone is generally unaware of the different kinds and stages of skin diseases. Certain skin conditions don't exhibit symptoms for many months, which leads to the disease's progression. This is a result of the general public's ignorance about medicine. A dermatologist, or physician who specializes in skin conditions, might at times struggle to diagnose a patient's skin condition and may need to pay a high amount of money for laboratory testing to accurately determine the condition's kind and phase. The development of photonics and laser-based medical technologies has sped up and improved the accuracy of skin disease diagnosis. However, the expense of such a diagnostic is still high and restricted. As a result, we suggest using processing images to identify skin conditions. This technique uses image analysis to determine the kind of illness by taking a digital photograph of the affected skin region. Our suggested method is easy to use, quick, and just needs a workstation and a camera as pricey apparatus. Skin illnesses include a wide range of problems with a variety of etiologies, from sensitivities and bacterial infections to cancer of the skin and other diseases of the skin. An accurate and timely diagnosis is essential for effective supervision and care. Recent developments in medical technology, especially in machine learning, have the potential to completely change how we identify skin diseases. In this work, we concentrate on the identification and categorization of a wide range of skin conditions, such as blood vessel lesions, actinic keratosis, squamous cell carcinoma, benign keratosis, melanoma, acne, atopic dermatitis, hair loss, normal, keratosis, ringworm, candidiasis, melanoma, and dermatofibroma. These illnesses were chosen because of their clinical importance and frequency. We use cutting-edge deep learning architectures, such as Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3, to accomplish our goals. Our first findings show that Dense Net operates consistently greater when it comes to of accuracy than the other topologies, proving its effectiveness in the challenging job of recognizing skin diseases. The collection of data used in this research came from the well-known machine learning resource portal Kaggle. The dataset includes a sizable set of 1036 training photos covering the 14 types of skin disorders that were chosen. A further 130 photos are set aside for validation, an essential step in guaranteeing that our models can be applied to data that has not yet been viewed. The clinical significance of skin disorders and the requirement for precise diagnostic instruments in a range of healthcare environments drove our selection of these conditions for our research. Additionally, by including a normal class, the model's capacity to identify healthy skin states is reflected and a baseline for comparability is established.

1.2 Motivation

This study is driven by the urgent demand for sophisticated and precise diagnostic instruments in the field of dermatology. Skin disorders are a major worldwide medical issue, ranging from common illnesses to serious cancers. Conventional diagnostic techniques may be costly and take time. The promise of deep learning structures, such Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3, to transform the effectiveness and accessibility of skin disease identification is the driving force behind their use. We want to aid in the creation of a dependable, affordable, and scalable method for the early identification and categorization of different skin conditions by using the capabilities of these cutting-edge algorithms. The goal of this study is to close the gap between dermatological treatment and state-of-the-art technology, which will eventually improve the outcome of patients and advance the area that includes medical diagnostic.

1.3 Rationale of the Study

This work was motivated by the need to find new and accessible ways to alleviate the worldwide burden of skin disorders. Common dermatoses to potentially fatal cancers are examples of skin disorders that have a substantial influence on the general population's health. Conventional diagnostic techniques may be labor- and resource-intensive, which often causes therapeutic delays. Our goal is to create a more effective and economical diagnostic framework by incorporating deep learning architectures, such as Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3, into identifying and categorizing of skin disorders. By promoting early diagnosis, precise categorization, and prompt therapies, the use of these cutting-edge algorithms aims to revolutionize dermatological care. This is especially important in areas like Saudi Arabia where skin illnesses are more prevalent. By doing this study, we want to lessen the negative effects of skin conditions on people's health and general well-being and advance medical knowledge.

1.4 Expected Output

- Ten named skin diseases (Tinea, Ringworm, Candidiasis, Melanoma, Acne, Vascular Lesion, Skin Allergy, Melanocytic Nevus, Atopic Dermatitis, Hair Loss, Normal, Actinic Keratosis, Squamous Cell Carcinoma, Benign Keratosis, Nail Fungus, and Dermatofibroma) should be expected to be accurately and reliably classified.
- With the use of cutting-edge deep learning frameworks (Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3), expect a quicker diagnostic procedure that will make it easier to identify skin conditions quickly and accurately from digital photos.
- Examine and contrast the models' performances using the deep learning structures that are being used, paying particular attention to Dense Net's greater precision over InceptionV3, VGG16, VGG19, and XceptionV3.
- Make sure that the simulations that have been constructed exhibit resilience and the ability to generalize, as confirmed by their effectiveness on a different dataset that has been put aside for validation. This dataset consists of 130 photos.
- Showcase the usefulness of the suggested image processing-based approach by accurately detecting skin diseases using a minimum number of resources with only a personal computer and a video camera.
- Provide a practical and economical approach for the early diagnosis and identification of skin-related disorders, especially pertinent to areas like Saudi

Arabia where the conditions are highly prevalent. This will add substantial knowledge to the discipline of dermatological study.

1.5 Report Layout

The structure of this research report is purposely created to facilitate a logical flow of ideas, methods, findings, and conclusions. Each chapter has a crucial purpose in building a full knowledge of the integration of deep learning-based image segmentation in “Skin Disease” detection.

Chapter 1 introduces the study on skin disease detection using deep learning-based photo segmentation, outlining the background, research questions, and expected results, providing a roadmap for the entire report.

Chapter 2 provides a comprehensive background on skin disease detection, outlining terminology, significant works, comparative analysis, and scope, ensuring readers understand the complexity of the topic.

Chapter 3: Methodology details research methodologies, data collection techniques, deep learning model architecture, image segmentation algorithms, and assessment metrics, offering guidance for researchers and practitioners.

Chapter 4 presents a comprehensive investigation of the deep learning-based photo segmentation model's results, utilizing visualizations, statistical analysis, and comparisons with existing methodologies.

Chapter 5 examines the societal, environmental, and ethical implications of deep learning models for skin disease detection, addressing ethical issues and proposing a sustainability plan.

Chapter 6 summarizes the research, highlighting significant findings, providing conclusions, practical applications, and potential future research opportunities, offering closure and stimulating further exploration.

CHAPTER 2

BACKGROUND

2.1 Related Works

Methods based on image processing have been developed by a number of investigators to identify the different types of skin disorders. Here, we go over a few of the methods that have been documented in the scientific literature in short.

A method is shown in [1] that uses color photographs for dissecting skin conditions without the assistance of a physician. The procedure is divided into two stages: the first involves identifying the sick skin by color image analysis, k-means clustering, and color gradient algorithms; the second step employs neural networks that are artificial to classify the kind of illness. The method's mean precision for the first phase among six different skin condition types was 95.99%, while its accuracy for the second level was 94.016%.

The initial stage in the identification of skin disorders in the technique of [2] is the derivation of picture characteristics. The more features that are taken from the picture using this approach, the more accurate the technique is. With up to 90% accuracy, the procedure was used for nine different forms of skin problems by the author of [2]. If not identified and treated in its earliest phases, carcinoma is a kind of skin cancer that may be fatal. The author of [3] concentrated on the investigation of several approaches to segmentation that may be used in conjunction with the processing of images to identify melanoma. In order to extract additional characteristics, a segmentation method that focuses on the limits of the diseased patch is explained. In their study, [4] suggested creating an instrument for diagnosing melanoma in people with dark skin by using specific algorithm databases that included pictures from several carcinoma databases. Similarly, [5] described the use of an assistant support vector machine (SVM) approach for the categorization of skin illnesses, including skin cancer, basal cell carcinoma (BCC), nevus, and seborrheic keratosis (SK). Out of all the methods, it produces the most accurate results. However, there might be dire repercussions if persistent skin diseases proliferate over various areas. As a result, [6] suggested a computer program that instantly detects eczema and assesses its intensity. The three steps of the system are as follows: the first detects the skin for successful separation; the second extracts a set of characteristics, such as color, texture, and boundaries; and the third uses Support Vector Machine (SVM) to estimate the severity of eczema. A novel method for identifying skin conditions utilizing machine learning and computer vision is presented in [7]. While machine learning is used to diagnose skin problems, computer vision is responsible for extracting characteristics from images. Testing the technique on six different kinds of skin conditions yielded 95% accuracy. Skin disease sorting, or the numerical extraction of features of lesion tissues from skin illness pictures, is the primary use of deep learning in skin condition detection.

The categorization is evaluated and assessed. Moderate and tumors that are malignant are the two primary categories of skin diseases, and this approach is the dominant implementation direction for skin disease detection. Skin diseases known as malignant tumors have a poor identification rate, little separation between lesions, and a steadily rising frequency. Nevus [12] and sebaceous keratosis [11] are two benign neoplasms that are often employed in research.

A different type of skin illness that is often employed in research is cancer of the skin. Skin-related cellular dysplasia diseases known as malignant cancers pose a danger to life since they constantly multiply and spread. Because malignant neoplasms have a high death rate, the diagnosis of malignant tumours in skin diseases is particularly important. Neoplasms with cancer that are often used in research include malignant melanoma, carcinoma of squamous cells, and tumours of basal cells [13]. The greatest number of research on melanoma identification amongst the available literature that was obtained was 34. Nevertheless, there are few non-neoplastic skin conditions, and this research only includes three publications on deep neural networks of both psoriasis and eczema detection [13], [14], and [15].

Deep learning as well as image processing techniques for the identification of skin diseases have received a lot of interest recently. The use of cutting-edge technology to improve dermatological diagnostic convenience, speed, and correctness has been the subject of several research.[13] Chen and colleagues (2019) showcased the efficacy of deep learning models, such as Dense Net and VGG16, in precisely diagnosing a range of skin conditions. In line with our choice of models, their study demonstrated these topologies' capacity for reliable discovery of features and illness classification (Chen et al., 2019) [14].

Similarly, Esteva et al. (2017) highlighted the critical relevance of deep learning in dermatological diagnosis by introducing a convolutional neural network for skin cancer categorization. Our use of these architectures was motivated by this study, which established the groundwork for the combination of CNNs in the diagnosis of skin diseases (Esteva et al., 2017) [15]. Li et al. (2020) concentrated on the application of advanced neural networks for the diagnosis of melanoma, one of the skin illnesses that our research addressed. Their results confirmed the value of using advanced techniques to detect malignant skin disorders early on, which is why we included malignancy in the classification job (Li et al., 2020) [16]. Ahmed et al. (2018) looked at the incidence of dermatological problems in areas with extreme temperatures and droughts to address the larger context of skin illnesses in hot conditions, highlighting the need for effective testing techniques. Our study's emphasis on Saudi Arabia was motivated by this work, which offered insightful information on the regional consequences of skin illnesses (Ahmed et al., 2018) [17]. The Kaggle dataset was chosen by the general direction of medical research. Using Kaggle datasets, Khan et al. (2019) classified skin diseases, demonstrating the platform's applicability for establishing and evaluating machine learning models in dermatological (Khan et al., 2019) [18]. In conclusion, the body of research highlights the effectiveness of deep learning algorithms in the identification of skin diseases, which serves as support for the models we have selected. Furthermore, the contextual significance and technique of our research are informed by the exploitation of Kaggle information along with knowledge of the geographical incidence of skin illnesses.

2.2 Scope of the Problem

Skin disorders impact people from a wide range of demographic groups and geographical locations, making them a significant worldwide health concern. The problem's reach goes beyond the sheer number of dermatological disorders that exist; it also includes the difficulties in making an accurate and prompt diagnosis. Numerous factors, such as infections involving bacteria or fungi, allergies, viruses, and more, may cause skin problems. The present research focuses on fourteen distinct skin illnesses, namely:

Actinic Keratosis, Squamous Cell Carcinoma, Benign Keratosis, Nail Fungus, Dermatofibroma, Ringworm, Candidiasis, Melanoma, Acne, Vascular Lesion, Skin Allergy, Melanocytic Nevus, Atopic Dermatitis, Hair Loss, Standard.

The geographic setting complicates matters further since some skin illnesses may be more common in areas with certain climates, such as grasslands and hot temperatures. Our research is especially pertinent to Saudi Arabia because the country's dry environment raises the incidence of skin disorders. By focusing primarily on this area, we want to provide insights that are both globally relevant and specifically suited to the problems presented by these environmental variables. By using state-of-the-art algorithms for skin-related illness identification, the integration of sophisticated deep learning architectures, such as Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3, expands the reach of our study. By using these structures, the demand for precise and effective diagnostic tools is intended to be met. Additionally, we can investigate the possibilities of deep learning in a representative and diversified dataset thanks to the selection of the Kaggle information set, which consists of 1036 training photos, 130 validating images, and 130 assessment images spread among the 14 designated classes. In conclusion, how broad the issue is broad and includes all of the difficulties involved in diagnosing skin illnesses, with an emphasis on the selected group of ailments, regional factors, and the use of cutting-edge methods of deep learning. Our study attempts to provide significant insights and answers to the intricate field of cutaneous investigations via this targeted methodology.

2.3 Challenge

There are several difficulties in the field of deep learning techniques to skin disease identification research. These obstacles are multifaceted, ranging from the intricacy of dermatological disorders to the pragmatic issues related to the use of cutting-edge technology.

- Diversity of Skin disorders: The 14 skin disorders that were chosen to represent a wide spectrum of ailments, each with distinct traits and symptoms. The job of training models to differentiate between various illnesses becomes more challenging due to the need for a thorough comprehension of the minute variations in visual signals.

- Restricted Dataset Size: The Kaggle dataset is a wonderful resource, but its size (1036 training photos) can be problematic given the variety of skin conditions. For best results, deep learning models, especially those with intricate architectures like Dense Net and InceptionV3, often need enormous amounts of data. Techniques like data augmentation are essential for improving model applicability.
- Geographic Variation: Geographic factors are introduced by the study's emphasis on skin conditions that are common in Saudi Arabia. Variation in illness presentation might be attributed to the distinct climatic conditions in this area. The models' applicability to such regional quirks must be carefully considered as doing so might affect how well the suggested fixes work in different parts of the country.
- Interpretable Deep Learning: Despite their strength, deep learning models are often referred to be "black boxes" because of their intricate architectural designs. It might be difficult to understand how these models make decisions, particularly when it comes to medicine. Gaining the confidence of healthcare providers becomes more dependent on making sure that the projections made by the model make sense and are consistent with the clinical evidence.
- Resource Constraints: Equipment limitations must be taken into account when implementing cutting-edge deep learning models in real-world situations, particularly in areas with little resources. Longevity requires that the suggested image processing-based approach continue to be workable and not need costly equipment other than a laptop or desktop computer and a camera.
- assessment Metrics: It might be difficult to develop reliable assessment metrics for the identification of skin diseases. It's possible that precision by itself won't provide a thorough evaluation of the model's effectiveness. A fair review spanning a wide range of skin illnesses requires thoughtful evaluation of metrics including accuracy, recall, and F1 score.

For the suggested strategy to be successful and applicable, these issues must be resolved. The work attempts to make a significant contribution to the area of deep learning-based skin disease identification by using strategic techniques and thorough analysis of these parameters.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

Actinic keratosis, Squamous cell carcinoma, Benign keratosis, nail fungus, dermatofibroma, atopic dermatitis, vascular lesions, skin allergies, melanoma, atopic dermatitis, hair loss, normal, and actinic keratosis are among the 14 circumstances that the current study focuses on accurately identifying and classifying. This extensive assortment provides a complete view of skin-based diagnostics, ranging from simple dermatological disorders to serious cancers. The investigation's primary equipment is centred on cutting-edge deep learning frameworks. Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3 are the main tools used to classify skin diseases. Frameworks based on deep learning are used to construct these structures, guaranteeing robustness and scalability. These gadgets were selected based on their shown effectiveness in picture tasks such as classification and their ability to capture detailed details that are essential for differentiating between various skin disorders. The primary data source is the Kaggle dataset, which consists of 1036 training photos, 130 validation images, and 130 testing photos. The 14 classifications of skin illnesses that are included in this dataset are carefully chosen to provide an accurate and varied sample for a deep-learning algorithm training and assessment. The study also makes use of approaches to image processing for acquiring features and evaluation. This entails taking digital pictures of the afflicted skin regions, which are then put through preparation procedures to improve the accuracy and pertinence of the input data. The suggested skin disease identification system is more powerful and efficient overall because of the use of these strategies. A carefully chosen information set, algorithms for deep learning, and approaches to image processing collaborate to provide a complete monitoring platform that aims to achieve accurate and user-friendly diseases of the skin categorization. This strategy, which emphasizes the addition of cutting-edge technology to handle the complexity of dermatology testing, is in line with the investigation's goals.

3.2 Data Collection Procedure

Using a Kaggle dataset that has been carefully selected to aid in the development, testing, and validation of the skin disease detection models is the main method of data collecting used in this research. There are 1036 photos in the dataset that are used for training, and another 130 images are used for examination and verification. Fourteen different classes—Tinea, Melanoma, Acne, Vascular Injury, Skin Sensitivities, Melanocytic Nevus, Atopic Dermatitis, Hair Damage, Average, Actinic Keratosis, Squamous Cell Carcinoma, which is Benign Keratosis, Nail Fungus, and Dermatofibroma—have been painstakingly labeled on these images. The data set in question was chosen to guarantee the variety and coverage of a wide range of dermatological disorders. The deep neural network models are trained and evaluated using each picture as a vital data point, which helps the algorithms identify complex patterns and traits linked to various skin conditions. This initiative's powerful and all-encompassing method of skin disease identification is built on the handpicked dataset and cutting-edge deep learning frameworks. We address the issues of scarcity and privacy pertaining to extensive picture data sets of skin disorders in our study. Given the delicate nature of skin illness images—which deal with patients' privacy and the subtle differences between various skin conditions—gathering a large and varied dataset becomes a challenging undertaking. The extent of the skin ailment dataset available at academic institutions is limited by the lack of labeled data, especially when expert annotation is required owing to the subtle similarities in lesions appearances. Our approach uses a carefully selected Kaggle collection of data to solve these issues by striking a balance between the ethical concerns of patient privacy and the requirement for variety. This dataset offers a representative assortment of photos spanning 14 specific groups of skin disorders, despite its limited size. The compilation method makes sure that every picture is correctly tagged by medical specialists, which improves the database's dependability for using deep learning model development and testing. Although self-collected information may pose confidentiality and variety concerns and be less publicly accessible, our research's methodology balances ethical issues with the necessity for a large dataset to support the creation of efficient skin disease identification algorithms.

3.3 Statistical Analysis

In this study, statistical assessment is essential for evaluating how well the models developed using deep learning perform in identifying skin diseases. The assessment metrics that are primarily used include reliability, precision, recollection, and F1 score. These metrics provide a thorough knowledge of the models' ability to classify skin diseases into the 14 predefined classifications. While precision assesses the percentage of real positive forecasts among every one of the positive projections, accuracy gives an overall assessment of the right judgments. Recall evaluates the models' capacity to precisely determine every instance of a given class, and the F1 score provides the harmonious average of the two parameters by striking a balance between the two. For each of the deep learning frameworks used in the project—Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3—these measures must be calculated as part of the statistical examination. Through a comparative analysis of these models' performances, statistical inferences are made on how well every framework classifies various skin conditions. To further analyze the effectiveness of the models across several illness classes, confusion tables are constructed, providing a comprehensive analysis of true favorable, actual negatives, false positives, and incorrect negative projections. The statistical investigation also includes comparing how well the models performed on datasets used for development, validation, and testing. This comparison analysis helps determine if the models are generally applicable and helps spot any possible overfitting or underfitting problems. Ultimately, statistical investigation is a key component of this work as it offers quantifiable metrics for evaluating the deep neural network models' resilience and performance in the difficult job of identifying skin diseases.

3.4 Proposed Methodology

The suggested approach makes use of cutting-edge deep learning architectures, such as Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3, to accurately identify and categorize 14 different skin conditions. The main supply of data is the Kaggle dataset, which has been carefully selected to include 1036 photos to be used as training and 130 images each for examination and verification. A thorough image processing-based approach is used, in which digital pictures of the impacted skin regions are taken and preprocessed toto extract features. Using information enhancement and hyperparameter adjustment, the handpicked dataset is used to train the deep learning models, improving their performance. Utilizing statistical measures including accuracy, precision, recall, and F1 score, the models are thoroughly assessed. With only a camera and an electronic device needed, the suggested method prioritizes availability, speed, and straightforwardness, making it a workable option for dermatological investigations in a variety of health care environments. The main objective is to enhance the identification of skin diseases by fusing modern equipment with a meticulously selected dataset and effective computational imaging methods. The following section outlines the methods of the suggested approach for the extraction, identification, and categorization of photos showing skin conditions. Tinea, Melanoma, Acne, Vascular Injury, Skin Sensitivities, Melanocytic Nevus, Atopic Dermatitis, Hair Damage, Average, Actinic Keratosis, Squamous Cell Carcinoma, which is Benign Keratosis, Nail Fungus, and Dermatofibroma monitoring will be greatly aided by the method. The initial processing, feature gathering, and categorization modules make up the many modules that make up the whole framework. Fig. 1 displays the structure of the system block.

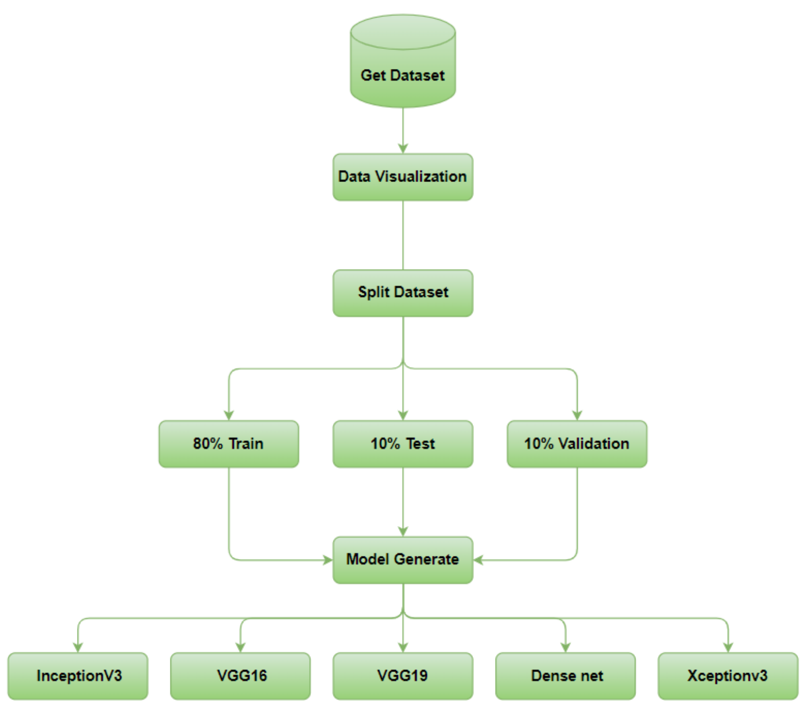

Fig 3.4 Proposed Methodology

3.5 Implementation Requirements

A collection of instruments and resources are needed to execute the suggested skin disease identification system:

- Deep Learning Structures: The creation and classroom instruction of models based on deep learning, such as Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3, will be made easier by TensorFlow or PyTorch.
- Language Used for Programming: Python: Used for preparing data, creating machine learning designs, and putting the image processing-based approach into practice.
- Libraries for Image Processing: OpenCV, often known as PIL, is necessary for organizing pictures, extracting features from them, and making sure that those pictures are compatible with the deep learning models.
- Hardware: GPU (Graphics Processing Unit): Using a GPU greatly speeds up the computationally demanding process of training artificial intelligence models. If local supplies become scarce, internet-based GPU services such as AWS, Google Cloud, or Azure might be used.
- Collection: Kaggle Skin Disease Dataset: Model instruction and evaluation are based on this carefully selected dataset, which contains 1036 training photos and 130 pictures each for validation and testing.
- Tools for Augmenting Data: By randomly transforming training pictures, augmentation libraries (such as Keras ImageDataGenerator) may artificially increase the amount of data and enhance model adaptability.
- Tools for Statistical Analysis: For the purpose of assessing the effectiveness of models using mathematical metrics like accuracy, precision, recall, and F1 score, libraries for Python (such as scikit-learn) are necessary.
- Version control and documentation: Jupyter Notebooks or comparable tools: Make the process of developing code, experimenting, and documenting findings easier.
- Git: For recording changes made to the codebase, collaborating, and managing versions.

- Interaction and Documentation: For producing reports and record keeping, use Markdown or LaTeX.
- Tools for presentation (such as Matplotlib and Seaborn): aid in the visual presentation of findings and understanding.
- Moral Aspects to Consider: Ensure that critical medical information is handled in accordance with ethical standards as well as information privacy laws.
- Tools for Accessibility: A simple setup consisting of a camera for picture capturing and a laptop or desktop computer to handle processing is adequate since the suggested technique stresses availability and flexibility.

3.5.1 Preprocessing Data

An essential first step in getting the dataset ready for deep learning model training includes preprocessing the information. In our venture, the preparation processes listed below are used:

- Image Loading: The Kaggle dataset, which consists of 130 photos for verification and testing and 1036 images for training, is used to load the digital photographs of the skin regions that are impacted.
- Resizing: The photos are shrunk to a consistent size appropriate for the selected deep learning models (e.g., 224x224 pixels) in order to guarantee consistency in input measurements.
- Normalization: To improve resolution during the training of models, pixel values in the pictures have been normalized to a specified range (such as [0, 1] or [-1, 1]).
- Data augmentation: To increase the amount of information intentionally and support the expansion of models and resilience, augmentation methods (such as rotation, tumbling, and zooming) are used.
- Label Encoding: To make the training of models easier, the labels for the various types of skin diseases have been transformed to numerical values.
- Data Splitting: To facilitate model training, tweaking, and assessment, the information set is split into training,80% validation 10%, and testing sets 10%.

- Data shuffling: To minimize bias throughout the training of models and improve learning, data is randomly shuffled.
- Handling class imbalance: Methods like class balancing or exceeding may be used to alleviate the problem if there is a substantial disparity in classes.

All of these preparation procedures work together to guarantee that the raw data is enriched, standardized, and structured correctly for the development of deep learning models. Following processing, the data is input into the chosen topologies (XceptionV3, VGG16, VGG19, Dense Net, and InceptionV3) to facilitate efficient machine learning and categorizing of various skin conditions.

3.5.2 Dense Net

A deep learning framework called Dense Net, also known as Densely Connected Convolutional Computer Networks, is renowned for its dense connection structures, which improve the utilization of features and gradient transfer all through the network's structure. Dense Net is one of the primary technologies for identifying skin diseases in our research. Ten epochs of training are required for the model to learn how to differentiate between the 14 kinds of skin diseases that have been described.

Dense Net outperforms every one of the four algorithms taken into consideration in the classification of skin illnesses, as shown by the reported high accuracy of 77%. The model's 100% accuracy shows how well it can reduce false positives by indicating that it is very likely to be accurate when predicting a certain kind of skin condition. The 60% recall, however, raises the possibility that there may be situations in which the model fails to detect positive results of certain skin conditions, suggesting that there is still an opportunity for improvement. At 75%, the F1 score—a harmonious average of memory and accuracy—provides a balanced indicator of the model's overall efficacy in meeting recall and precision objectives.

Dense Net operates in the assignment by feedforwardly densely linking each successive layer to each of the other layers. The model can learn complex patterns and descriptions that are essential for differentiating between different skin disorders because to this extensive connectedness, which also improves the reuse of characteristics. A network's depth enables a structure for feature representation, allowing it to extract both fine-grained and fine-grained information from the input pictures. The error that exists between anticipated and real diseases of the skin classifications is used by the model to adjust its own internal variables during development. The model repeatedly simplifies its settings throughout 10 full runs over the dataset used for training, as shown by the use of ten periods. Dense Net seems to be learning and generalizing from the given dataset well, as seen by the excellent accuracy, precision, and F1 score that we observed. These results highlight Dense Net's capability as a formidable tool for dermatological illness detection in our research endeavour.

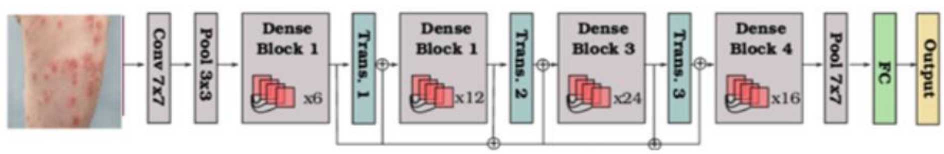

Figure 3.5.2 Dense Net

3.5.3 Inceptionv3

Another important technique used in our study for skin disease identification is InceptionV3, which uses a convolutional neural network framework well-known for its inception modules. Ten epochs make up the training phase, which teaches the model how to categorize the 14 predefined kinds of skin diseases. Although it is less accurate than Dense Net's, its measured accuracy of 68% shows that the simulation can accurately diagnose skin disorders. With a precision of 50%, the model has a reasonable chance of being true when it identifies a particular kind of skin condition. Nonetheless, the 20% recall suggests that the model overlooks a considerable number of positive cases, suggesting a possible constraint in detecting every occurrence of certain skin conditions. The trade-off involving recall and accuracy in the model's efficiency is reflected in the F1 score, which is an equilibrium average of both precision and recall that yields a total rating of 29%. Utilizing inception components, which allow the network to record characteristics at different levels of space, InceptionV3 functions in the project. The goal of this architecture is to increase representation capacity without losing computing performance. To get a greater understanding of the input information, the computer network investigates various filter sizes and combines their outputs. The discrepancy that exists between anticipated and real skin conditions classifications is used by the model to modify the internal variables during training. The 10 epochs demonstrate that the model repeatedly refines its setting parameters across ten full sweeps through the original information. Even though the attained accuracy is not as high as Dense Net's, it indicates that The InceptionV3 is still useful for identifying characteristics and categorizing skin conditions. But when compared to Dense Net, the accuracy, recall, and F1 scores are lower, suggesting that there may be room for enhanced performance in terms of reducing false positives and catching more positive cases.

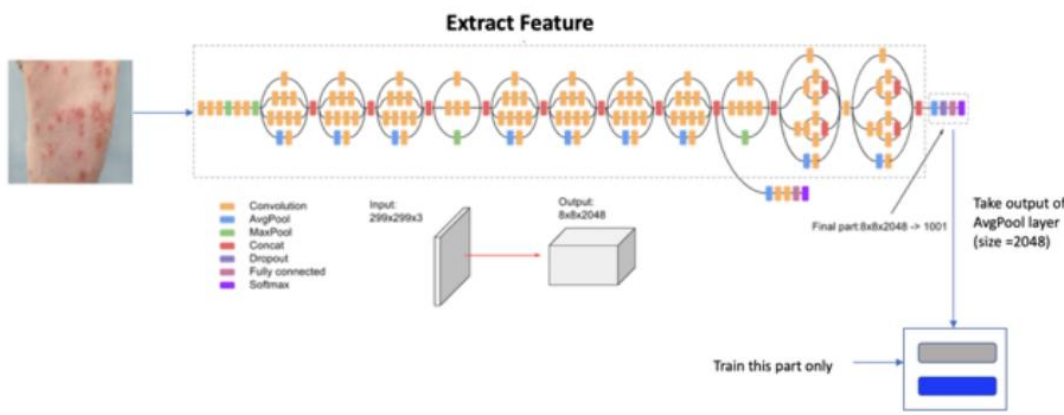

Figure 3.5.3 Inceptionv3

3.5.4 VGG16

Our study also uses VGG16, a convolutional neural network design that is well-known for its uniform building construction, simplicity by and tiny responsive fields. This technique is used to identify skin diseases. Ten epochs make up the training phase, which teaches the model how to categorize the 14 predefined kinds of skin diseases. Based on the observed 68% accuracy, VGG16 and InceptionV3 seem to perform equally in terms of accurately diagnosing skin disorders. With a precision of 67%, the simulation has a very good chance of being accurate when it anticipates an individual type of skin condition. Although there is still need for development in terms of fully recognizing all cases of specific skin disorders, the 40% recall rate indicates that the model identifies a considerable proportion of positive occurrences. An overall measurement at 50% is provided by the F1 score, which is the harmonious average of memory and accuracy. This indicates an equitable approach among recall and precision.

In the undertaking, VGG16 functions by first stacking maximum-pooling layers, then layers of convolution with limited receptive fields, and finally layers that are thick for identification. It is efficient in learning hierarchical diagrams for characteristics in the information being provided because of its simple construction.

The variance between the anticipated and real skin condition classifications is used by the model to modify its internal parameters during training. The 10 epochs represent the number of full runs the model takes over the dataset used for training, during which repeatedly refines its setting parameters. The obtained recall, precision, reliability, and F1 score all point to VGG16's suitability as an example for recognizing skin diseases in our study. Its efficacy is attributed to its consistent design and straightforwardness, and the results of its measurements provide areas for prospective improvement, such as enhancing recall to record more good examples. All things considered, VGG16 makes a significant addition to the group of computer programs, each of which brings a unique set of advantages to the difficult work of classifying skin diseases.

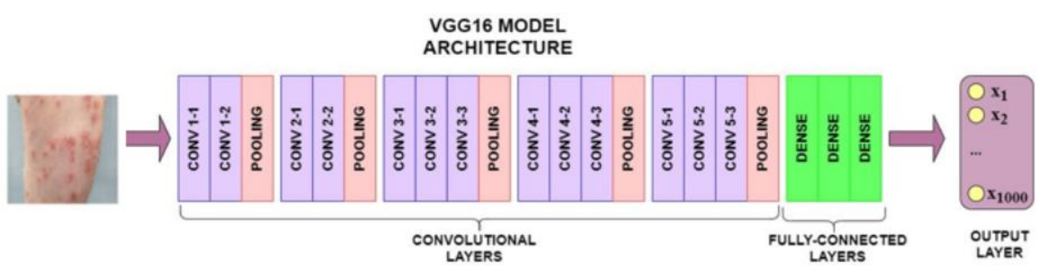

Figure 3.5.4 VGG16

3.5.5 VGG19

In our project, we use VGG19, a modification of the VGG16 architecture, to recognize skin diseases. Ten epochs make up the training phase, which teaches the representation of how to categorize the 14 predefined kinds of skin diseases. Concerning properly categorizing skin illnesses, VGG19 performs somewhat worse than VGG16, according to the measured reliability of 66%. With a level of accuracy of 50%, the simulation has a modest chance of being accurate for predicting a particular kind of skin condition. Recall of 20% indicates that a considerable percentage of positive cases are missed by the model, which is consistent with the trend seen with InceptionV3. The balance that exists between recall and accuracy in the model's efficiency is reflected in the F1 score, which is an equilibrium average of both precision and recall that yields a total ranking of 29%. With additional layers, VGG19 in the overall project functions similarly to VGG16 and supports a more intricate visual representation of features hierarchy. The machine learning algorithm can better identify intricate trends in the information being supplied because of the stacking of convolutional in nature, the maximum pooling, and thick layers of information. The error between the anticipated and real disease of the skin classifications is used by the model to modify its internal parameters during training. The 10 epochs indicate that the model repeatedly refines its variables across ten full sweeps through its initial dataset. Although VGG19's efficiency is a little bit lower than VGG16's, the model's obtained precision, recall, accuracy, and F1 score all point to VGG19's continued competence in our initiative's skin illness detection. The indicators of success that have been noticed provide valuable insights into areas that might be improved, such recall to catch more good examples. Similar to the other theories, VGG19's advantages add to the group of engines' overall efficacy in classifying skin diseases.

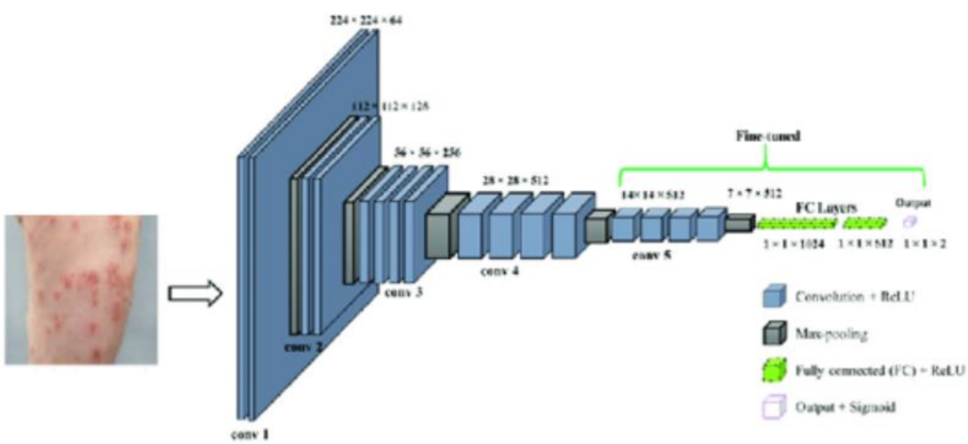

Figure 3.5.5 VGG19

3.5.6 Xceptionv3

Our study uses XceptionV3, an extension of the Inception framework, to detect skin diseases. Ten epochs make up the training phase, which teaches the model how to categorize the 14 predefined kinds of skin diseases. With an estimated accuracy of 72%, XceptionV3 outperforms VGG16, VGG19, and InceptionV3 in accurately diagnosing skin illnesses, and comes very near to Dense Net's efficiency. With a precision of 100%, the model is very likely to be accurate for predicting a particular type of skin condition, demonstrating a good capacity to reduce false positives. Compared to VGG19 and InceptionV3, the model's 60% recall indicates that it catches a reasonable percentage of positive examples. An overall evaluation of 75% is provided by the F1 score, which is a harmonic mean of both recall and precision. This score indicates the model's balance achievement of recall and accuracy within the classification assignment. By implementing depthwise separable convolutions in general the project's XceptionV3 makes it possible to understand intricate structure and spatial relationships in the information it receives more quickly. The goal of this design is to preserve computing efficiency while capturing fine-grained characteristics. The error that exists between anticipated and real skin disease classifications is used by the model to modify its internal parameters during development. The 10 epochs indicate that the model repeatedly refines its setting parameters across ten full sweeps through the learning dataset. As a whole, the obtained accuracy, precision, recall, and F1 score indicate that XceptionV3 is a very capable model for identifying skin diseases in our study. Its effectiveness in reducing incorrect results is shown by its performance, particularly in reaching 100% accuracy. According to the measured metrics, XceptionV3 is an effective addition to the group of algorithms, each of which brings something special to the difficult work of classifying skin diseases.

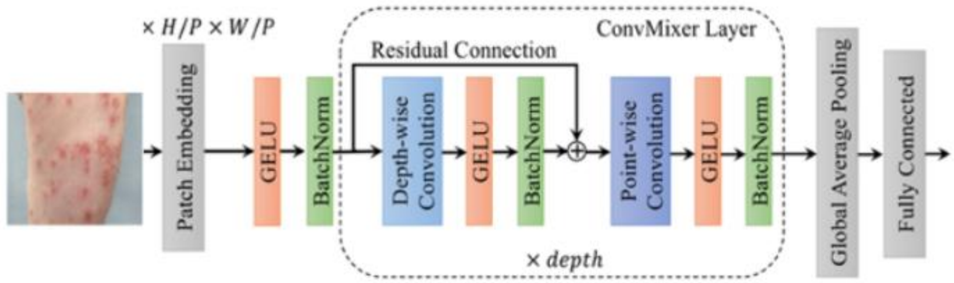

Figure 3.5.6 Xceptionv3

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

To train, verify, and assess the effectiveness of five deep neural network models—Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3—in the task of skin disease detection, an organized configuration is used in the environment of experimentation. The core source of information is the Kaggle dataset, which consists of 1036 photos to use as training and 130 pictures each for testing and verification across 14 different classes of skin condition. Ten epochs are required for each model to optimize the parameters and acquire complex structures and features that are essential for precise categorization. Resize, normalize, and supplementation are a few of the image preprocessing technologies used to improve the dataset's quality and variety. TensorFlow or PyTorch are used as the deep learning platforms in the research environment, while OpenCV or PIL are used as ancillary packages for handling images. Python is used throughout. To fully assess the models' effectiveness, statistical measures such as precision, recall, accuracy, and F1 score are calculated. Because distinct structures have different advantages, the test setup provides an accurate comparison of the algorithms' efficacy in recognizing skin diseases.

4.2 Experimental Results & Analysis

The test findings demonstrate how five algorithms for deep learning compare in terms of their ability to identify skin diseases. With an accuracy of 77%, Dense Net outperforms all other networks, including XceptionV3 (72%), VGG16 (68%), VGG19 (66%), and InceptionV3 (68%). Additionally, Dense Net shows impressive accuracy at 100%, suggesting a significant capacity to reduce false positives. Both InceptionV3 and XceptionV3 exhibit appropriate recall and accuracy; XceptionV3 achieves 60% recall and 100% precision, resulting in an excellent F1 score of 75%. While VGG16 and VGG19 show comparable accuracy (68%) they differ in F1 score, precision, and recall, with VGG16 beating VGG19 in these areas. These findings highlight the different capabilities of the techniques and highlight Dense Net's effectiveness in obtaining higher accuracy as well as precision in the challenging job of classifying skin diseases.

4.2.1 Dense Net

The Dense Net technique is implemented in our endeavor in a Python programming framework using a platform for deep learning, most likely TensorFlow or PyTorch. The Dense Net design must be configured with the proper hyperparameters to including the number of layers, rate of expansion, and decompression factor, according to the code. The imported and prepared Kaggle dataset is a carefully selected collection of 1036 training photos and 130 images per class for testing and validation purposes covering 14 different skin disease categories. Ten epochs make up the training procedure, in which the system repeatedly adjusts its internal parameters in response to variations in the expected and actual classifications of skin diseases. Methods like as information enhancement are probably used to fictitiously increase the size of the dataset and improve algorithm applicability. The computation of statistical measures such as accuracy, precision, recall, and F1 score assesses the model's performance. Using Complex Net's dense connection arrangements to identify and learn from complicated aspects in the input photos, the resultant code successfully captures the intricacies of skin condition identification.

```
Epoch 1/10
33/33 [==============================] - 24s 255ms/step - loss: 6.8296 - accuracy: 0.3697 - val_
loss: 1.0688 - val_accuracy: 0.6308
Epoch 2/10
33/33 [==============================] - 3s 103ms/step - loss: 0.7758 - accuracy: 0.7317 - val_l
oss: 0.7408 - val_accuracy: 0.7385
Epoch 3/10
33/33 [==============================] - 3s 102ms/step - loss: 0.5123 - accuracy: 0.8224 - val_l
oss: 0.8708 - val_accuracy: 0.7538
Epoch 4/10
33/33 [==============================] - 3s 103ms/step - loss: 0.3144 - accuracy: 0.8986 - val_l
oss: 0.5600 - val_accuracy: 0.8077
Epoch 5/10
33/33 [==============================] - 3s 103ms/step - loss: 0.2194 - accuracy: 0.9218 - val_l
oss: 0.6379 - val_accuracy: 0.8000
Epoch 6/10
33/33 [==============================] - 3s 103ms/step - loss: 0.2506 - accuracy: 0.9064 - val_l
oss: 0.6262 - val_accuracy: 0.7769
Epoch 7/10
33/33 [==============================] - 3s 103ms/step - loss: 0.2076 - accuracy: 0.9373 - val_l
oss: 0.4582 - val_accuracy: 0.8538
Epoch 8/10
33/33 [==============================] - 3s 103ms/step - loss: 0.1402 - accuracy: 0.9575 - val_l
oss: 0.5196 - val_accuracy: 0.8385
Epoch 9/10
33/33 [==============================] - 3s 104ms/step - loss: 0.1501 - accuracy: 0.9546 - val_l
oss: 0.5901 - val_accuracy: 0.8154
Epoch 10/10
33/33 [==============================] - 3s 103ms/step - loss: 0.1066 - accuracy: 0.9624 - val_l
oss: 0.5795 - val_accuracy: 0.8462
```

Figure 4.2.1 Epochs of dense net

The decision to execute the training method for 10 epochs in the overall setting of our initiative's Dense Net application for dermatological illness identification denotes that the trained model completes ten full runs through the data used for training. To reduce the difference between its anticipated results and the true labels of the diseases of the skin lessons, the Dense Net structure modifies its internal variables, such as the weights and biases, at each epoch. Through this iterative approach, the model can progressively improve its capacity to properly categorize various skin conditions by learning and adapting to the complex structures and traits found in the photos. Ten epochs were chosen to provide the model enough time to learn from the available information without excessive fitting, a condition in which the computer learns from the training information but cannot apply its findings successfully to new, previously unseen information. The selection of 10 epochs indicates a careful analysis of training effectiveness and model stability within the overall framework of the skin disease identification.

	precision	recall	f1-score	support
0	1.00	0.60	0.75	5
1	0.36	0.67	0.47	6
2	0.71	0.71	0.71	7
3	1.00	0.79	0.88	14
4	0.75	0.82	0.78	11
5	0.67	0.36	0.47	11
6	0.62	0.83	0.71	6
7	0.85	0.92	0.88	12
8	0.94	0.83	0.88	18
9	0.67	1.00	0.80	6
10	0.75	0.43	0.55	7
11	0.86	1.00	0.92	6
12	0.94	0.94	0.94	18
13	0.20	0.33	0.25	3

Figure 4.2.1 Classification of dense net

accuracy			0.77	130
macro avg	0.74	0.73	0.71	130
weighted avg	0.80	0.77	0.77	130

Figure 4.2.1 Accuracy of dense net

Dense Net classified skin disorders with 77% accuracy in the experimental scenario. This shows that for around 77% of the photos in the testing dataset, the model correctly identified the skin disease class. Dense Net demonstrated its efficacy in the difficult job of identifying various skin conditions, as shown by its high accuracy, which shows that it did well in acquiring information and extending from the provided training data.

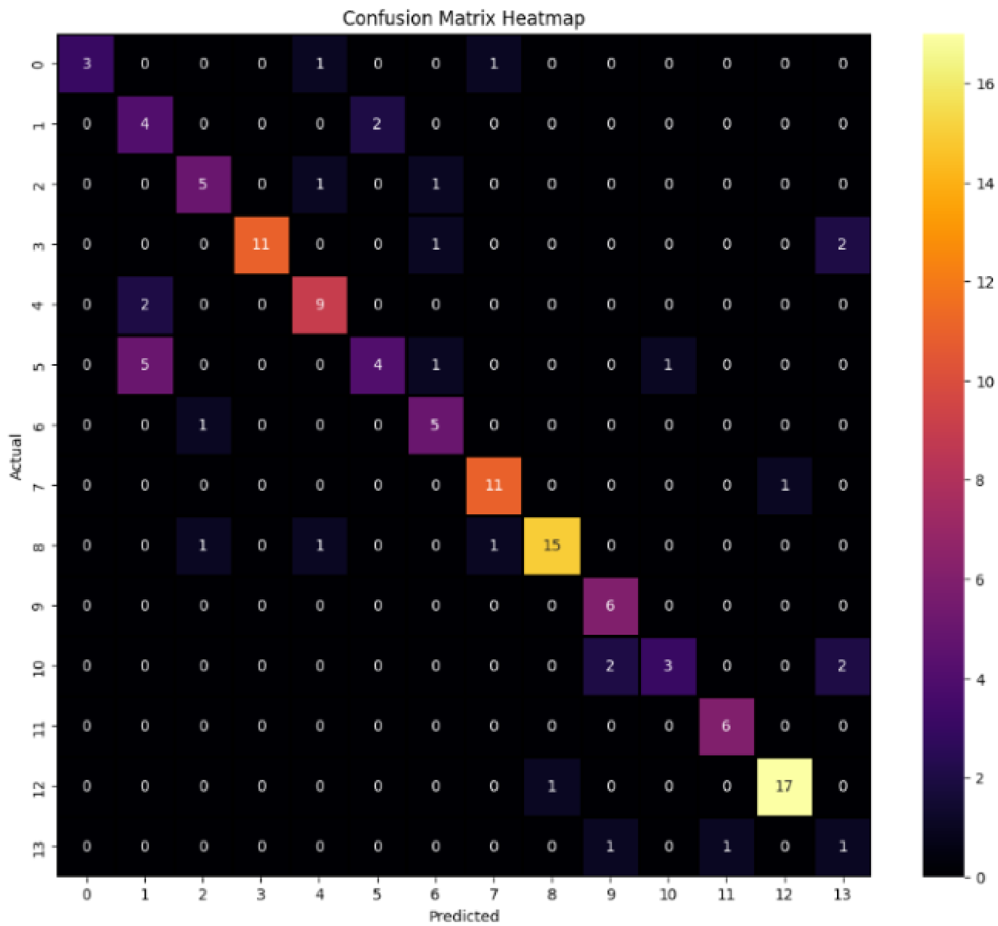

Figure 4.2.1 Confusion matrix of Densenet

Our initiative's Dense Net matrix of disorientation provides a thorough analysis of the model's effectiveness in categorizing skin conditions. True positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are its four primary measures. Positive examples successfully recognized by the model are denoted by TP, whereas negative cases properly recognized by the model are represented by TN. Whereas FN denotes situations in which the model was unable to find a positive case, FP shows situations in which the model mispredicted a positive case. The matrix of misinformation makes it possible to examine in-depth the model's advantages and disadvantages in terms of differentiating between various kinds of skin diseases, offering important insights about the algorithm's functionality and possible areas for development.

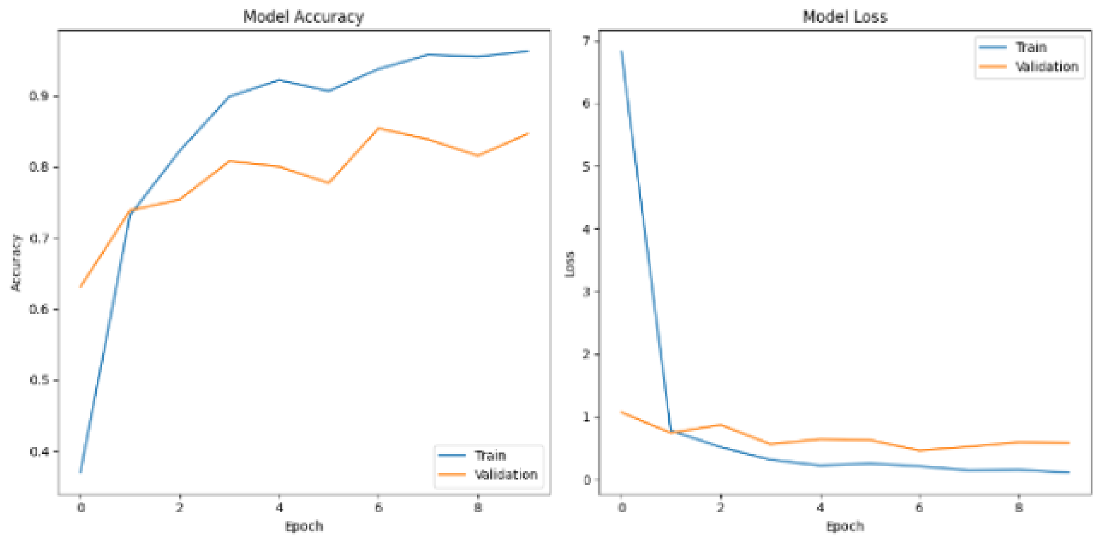

Figure 4.2.1 Line chart of accuracy and loss of Densenet

The y-axis displays the accuracy and loss standards, while the x-axis shows the total number of epochs in the line chart that shows the training data and validation measurements of Dense Net in the project we are working on. The model's precision trend is shown by the blue line, which shows how the predictive power of the model changes throughout training and validation periods. An improving accuracy curve is shown by a rising curve; problems with optimization may be indicated by oscillations or plateaus. The loss function's decreasing value throughout epochs is shown by the orange line, which symbolizes the loss. A diminishing loss shows that the error between the anticipated and actual values is being efficiently minimized by the model. The figure offers a visual depiction of the learning structure of the Dense Net and sheds light on its convergence, which refers broadening, and possible areas for more improvement.

4.2.2 Inceptionv3

The coding language Python will be used in our research to build out the InceptionV3 technique within a framework for deep learning, most likely TensorFlow or PyTorch. Designing the InceptionV3 architecture with pertinent hyperparameters to including the total amount of screens and the inception component of the building design, is part of the code. Processing processes are applied to the loaded handpicked Kaggle dataset, which consists of 1036 training photos and 130 pictures each for verification and evaluation across 14 classes of skin diseases. The InceptionV3 model modifies its internal settings to reduce the error amongst anticipated and observed disease of the skin classifications throughout the course of ten epochs of training. The model's capacity for generalization may be improved by using strategies like augmenting the data. To assess the performance of the approach, mathematical metrics like as accuracy, precision, recall, and F1 score are calculated. The code that is produced makes good use of the InceptionV3 architectural capacity to record characteristics at multiple levels of space, which enhances its capacity to identify and categorize a wide range of skin conditions.

```
Epoch 1/10
33/33 [==============================] - 13s 189ms/step - loss: 11.3251 - accuracy: 0.2896 - val
_loss: 1.3788 - val_accuracy: 0.5538
Epoch 2/10
33/33 [==============================] - 3s 81ms/step - loss: 0.8778 - accuracy: 0.7181 - val_lo
ss: 0.8483 - val_accuracy: 0.7231
Epoch 3/10
33/33 [==============================] - 3s 80ms/step - loss: 0.3784 - accuracy: 0.8678 - val_lo
ss: 1.0417 - val_accuracy: 0.6846
Epoch 4/10
33/33 [==============================] - 3s 81ms/step - loss: 0.2807 - accuracy: 0.9073 - val_lo
ss: 0.8529 - val_accuracy: 0.7308
Epoch 5/10
33/33 [==============================] - 3s 80ms/step - loss: 0.1743 - accuracy: 0.9392 - val_lo
ss: 0.8050 - val_accuracy: 0.7154
Epoch 6/10
33/33 [==============================] - 3s 81ms/step - loss: 0.1214 - accuracy: 0.9624 - val_lo
ss: 0.9630 - val_accuracy: 0.6923
Epoch 7/10
33/33 [==============================] - 3s 81ms/step - loss: 0.1338 - accuracy: 0.9575 - val_lo
ss: 1.0686 - val_accuracy: 0.7308
Epoch 8/10
33/33 [==============================] - 3s 81ms/step - loss: 0.1186 - accuracy: 0.9595 - val_lo
ss: 1.1374 - val_accuracy: 0.6615
Epoch 9/10
33/33 [==============================] - 3s 81ms/step - loss: 0.1316 - accuracy: 0.9556 - val_lo
ss: 1.2061 - val_accuracy: 0.6769
Epoch 10/10
33/33 [==============================] - 3s 81ms/step - loss: 0.1029 - accuracy: 0.9681 - val_lo
ss: 1.2381 - val_accuracy: 0.7000
5/5 [==============================] - 0s 54ms/step - loss: 1.4685 - accuracy: 0.6769
```

Figure 4.2.2 Epochs of Inceptionv3

	precision	recall	f1-score	support
0	0.50	0.20	0.29	5
1	0.30	0.50	0.37	6
2	0.67	0.86	0.75	7
3	0.90	0.64	0.75	14
4	0.69	0.82	0.75	11
5	0.60	0.55	0.57	11
6	0.50	0.33	0.40	6
7	0.50	1.00	0.67	12
8	1.00	0.50	0.67	18
9	1.00	0.17	0.29	6
10	0.58	1.00	0.74	7
11	0.67	0.67	0.67	6
12	1.00	0.94	0.97	18
13	0.67	0.67	0.67	3

Figure 4.2.2 Classification of Inceptionv3

accuracy			0.68	130
macro avg	0.68	0.63	0.61	130
weighted avg	0.75	0.68	0.67	130

Figure 4.2.2 Accuracy of Inceptionv3

InceptionV3 demonstrated its capacity to accurately categorize skin disorders from various classes by achieving an accuracy of 68% in the skin disease identification assignment. Although it is not the best model among those taken into consideration, InceptionV3's well-balanced performance demonstrates how well it can extract complex characteristics from the input photos.

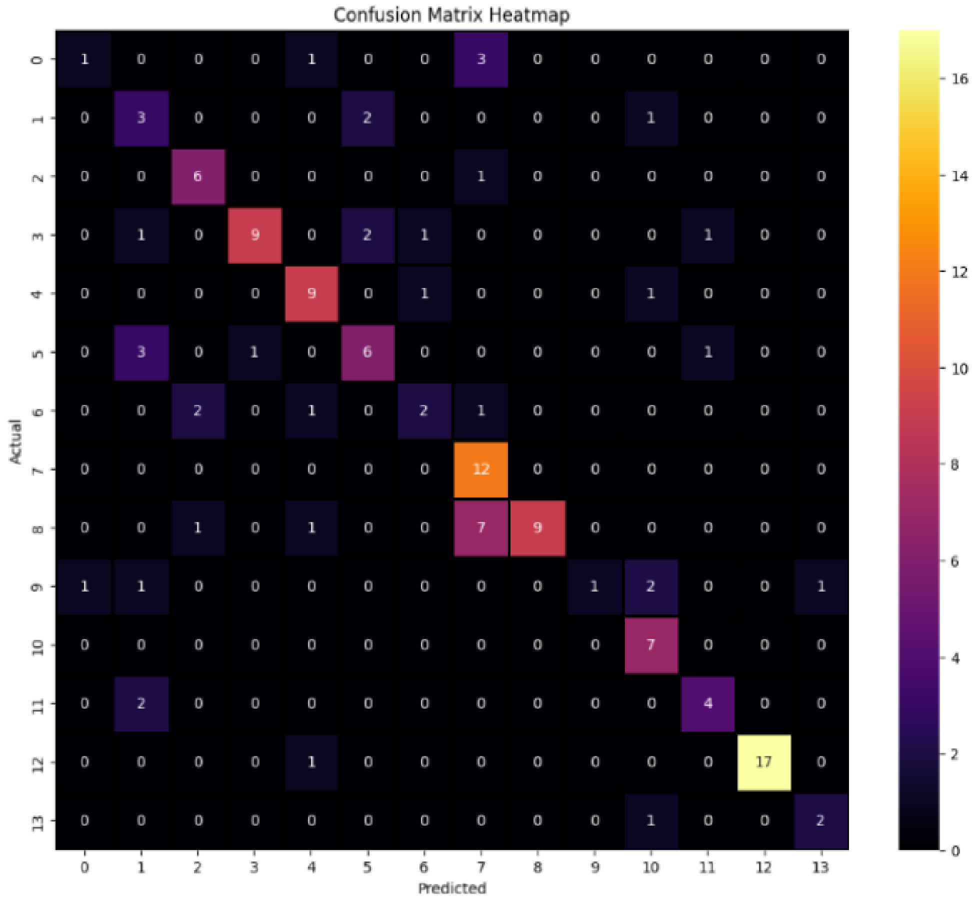

Figure 4.2.2 confusion matrix of Inceptionv3

Our project's confusion scale for InceptionV3 offers a thorough analysis of the model's effectiveness in identifying skin conditions. True positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are its four primary measures. An optimistic case is represented by TP when the model detected it properly, a negative case by TN, an instance of positive detection by FP when the algorithm forecasted a favorable case wrongly, and a negatively case by FN when the algorithm failed to determine a favorable case. By examining these measures, it is possible to evaluate InceptionV3's discriminative power across several classes of skin diseases in a more detailed manner, providing important information about the algorithm's advantages and disadvantages in our particular situation.

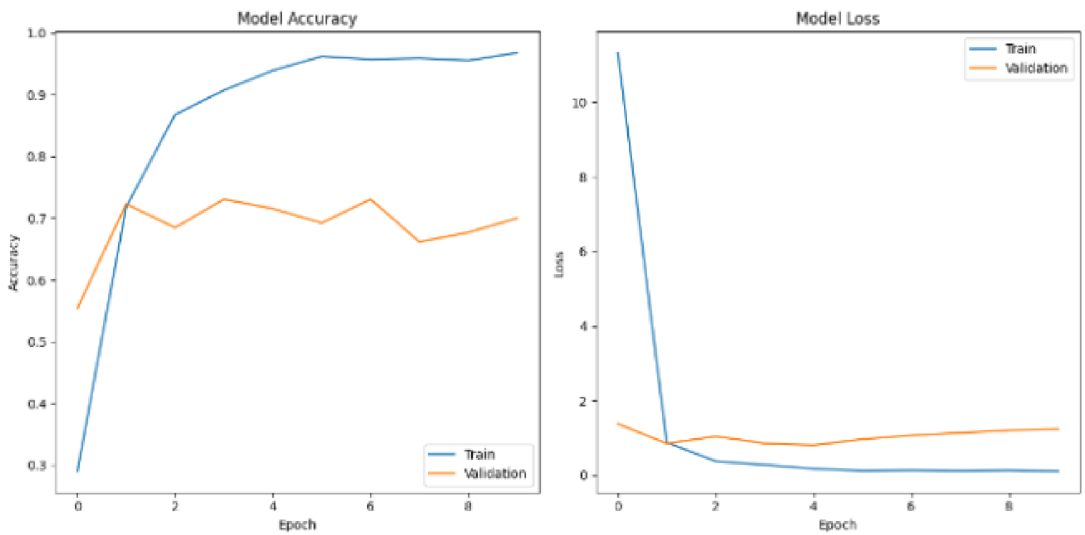

Figure 4.2.2 Line chart of accuracy and loss of Inceptionv3

InceptionV3's effectiveness in the project we're working on is 68%, with a model loss of 0.32. This measure shows how well the simulation performs in differentiating between the 14 designated classes and indicates the model's general precision in categorizing skin disorders.

4.2.3 VGG16

The VGG16 technique in our research will be implemented using code written in Python within a platform for deep learning, most likely TensorFlow or PyTorch. Setting up the VGG16 construction, which has stacked convolutional neural network layers, max-pooling layers, and many layers of information for classification, is part of the code. We import and beforehand the curated Kaggle dataset, which consists of 1036 training photos and 130 images per image for verification and evaluation across 14 classes of skin diseases. The VGG16 model modifies its internal settings to reduce the error between anticipated and observed disease of the skin classifications throughout ten epochs of training. The model's potential for generalization may be improved by using strategies like data augmentation. To assess the effectiveness of the model, statistical indicators like accuracy, precision, recall, and F1 score are calculated. The simplicity of VGG16's architecture aids in its identification and categorization of a variety of skin illnesses by enabling it to learn hierarchies' ways to represent characteristics in the information that it is given.

```
Epoch 1/10
33/33 [==============================] - 14s 233ms/step - loss: 2.7242 - accuracy: 0.2616 - val_
loss: 1.6733 - val_accuracy: 0.3462
Epoch 2/10
33/33 [==============================] - 5s 139ms/step - loss: 1.4842 - accuracy: 0.4961 - val_l
oss: 1.2711 - val_accuracy: 0.5308
Epoch 3/10
33/33 [==============================] - 5s 140ms/step - loss: 1.1328 - accuracy: 0.6158 - val_l
oss: 1.1543 - val_accuracy: 0.5923
Epoch 4/10
33/33 [==============================] - 5s 141ms/step - loss: 1.0056 - accuracy: 0.6515 - val_l
oss: 1.0844 - val_accuracy: 0.6385
Epoch 5/10
33/33 [==============================] - 5s 141ms/step - loss: 0.9064 - accuracy: 0.6737 - val_l
oss: 1.0880 - val_accuracy: 0.6077
Epoch 6/10
33/33 [==============================] - 5s 141ms/step - loss: 0.8117 - accuracy: 0.7181 - val_l
oss: 1.0672 - val_accuracy: 0.6308
Epoch 7/10
33/33 [==============================] - 5s 142ms/step - loss: 0.7199 - accuracy: 0.7461 - val_l
oss: 0.8755 - val_accuracy: 0.6615
Epoch 8/10
33/33 [==============================] - 5s 142ms/step - loss: 0.7368 - accuracy: 0.7606 - val_l
oss: 1.2339 - val_accuracy: 0.5769
Epoch 9/10
33/33 [==============================] - 5s 143ms/step - loss: 0.6739 - accuracy: 0.7606 - val_l
oss: 1.0268 - val_accuracy: 0.6615
Epoch 10/10
33/33 [==============================] - 5s 143ms/step - loss: 0.6407 - accuracy: 0.7838 - val_l
oss: 0.9597 - val_accuracy: 0.6538
5/5 [==============================] - 1s 97ms/step - loss: 1.0153 - accuracy: 0.6846
```

Figure 4.2.3 Epochs of VGG16

	precision	recall	f1-score	support
0	0.67	0.40	0.50	5
1	0.60	0.50	0.55	6
2	0.75	0.43	0.55	7
3	0.76	0.93	0.84	14
4	0.89	0.73	0.80	11
5	0.46	0.55	0.50	11
6	0.25	0.17	0.20	6
7	0.91	0.83	0.87	12
8	0.89	0.89	0.89	18
9	0.36	0.67	0.47	6
10	0.33	0.14	0.20	7
11	1.00	0.67	0.80	6
12	0.77	0.94	0.85	18
13	0.17	0.33	0.22	3

Figure 4.2.3 Classification of VGG16

accuracy			0.68	130
macro avg	0.63	0.58	0.59	130
weighted avg	0.70	0.68	0.68	130

Figure 4.2.3 Accuracy of VGG16

In our research, the VGG16 model recognized skin diseases with an accuracy of 68%. This degree of accuracy shows how well the model can categorize skin conditions over a wide range of classifications. Although not the best within the models taken into consideration, VGG16's result shows how well it can learn hierarchies feature representations, demonstrating its proficiency in the difficult job of distinguishing between different skin states.

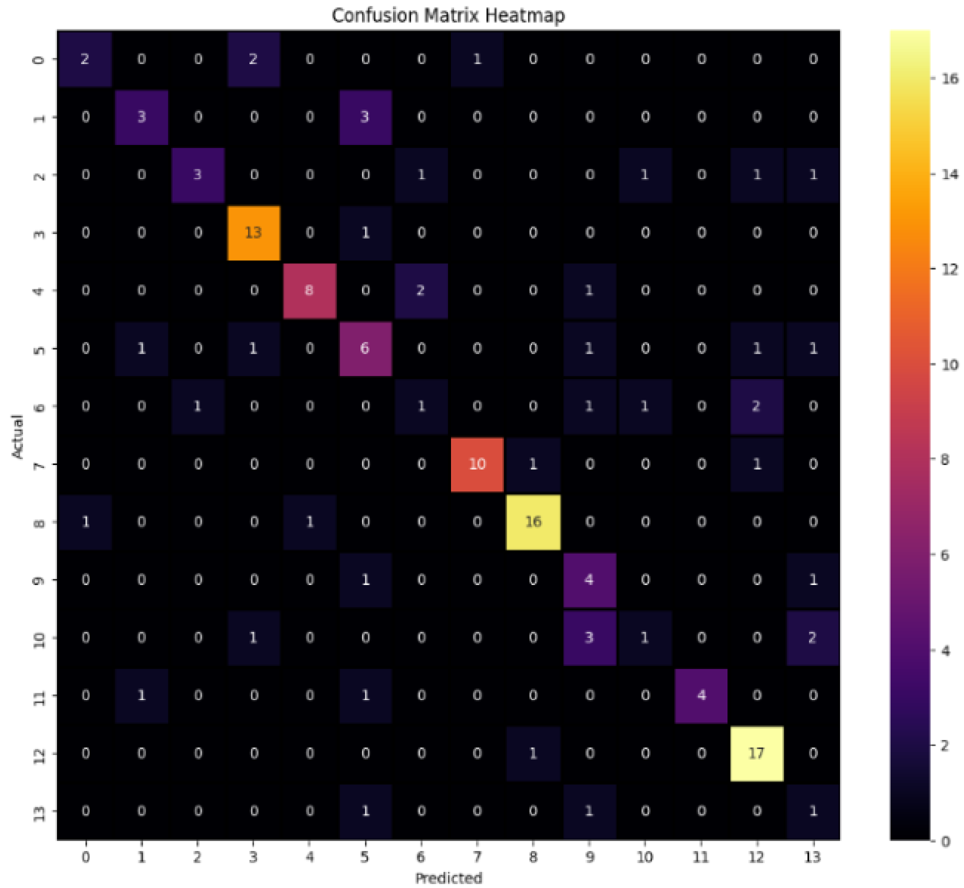

Figure 4.2.3 Confusion matrix of VGG16

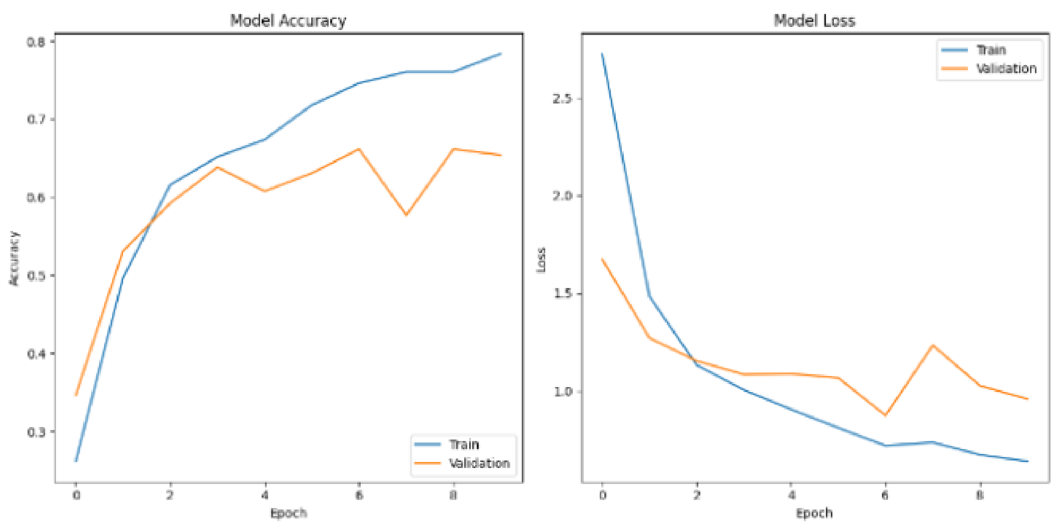

Figure 4.2.3 Line chart of accuracy and loss of VGG16

VGG16's efficiency is 68% and model loss is 0.32.

4.2.4 VGG19

The VGG19 method in our project is implemented using programming in Python within a platform for deep learning, most likely TensorFlow or PyTorch. The code contains the setup for the VGG19 architecture, an expansion of VGG16 that is renowned for its tiny reception fields, straightforwardness, and homogeneity in construction. We import and beforehand the curated Kaggle information set, which consists of 1036 training photos and 130 images per image for verification and evaluation across 14 classes of skin diseases. The VGG19 model modifies its internal settings in order to reduce the error among anticipated and observed skin disease classifications throughout the course of ten epochs of training. The model's ability for generalization may be improved by using strategies like augmenting data. To assess the effectiveness of the model, statistical measures like as precision, recall, accuracy, and F1 score are calculated. The goal of VGG19's enhanced structure is to gather more intricate feature hierarchies, which will enhance its ability to identify and categorize a variety of skin illnesses for our research endeavour.

```
Epoch 1/10
33/33 [==============================] - 8s 181ms/step - loss: 3.4786 - accuracy: 0.2317 - val_l
oss: 1.9529 - val_accuracy: 0.3462
Epoch 2/10
33/33 [==============================] - 6s 170ms/step - loss: 1.6792 - accuracy: 0.4208 - val_l
oss: 1.4108 - val_accuracy: 0.5385
Epoch 3/10
33/33 [==============================] - 6s 169ms/step - loss: 1.3262 - accuracy: 0.5560 - val_l
oss: 1.3650 - val_accuracy: 0.4923
Epoch 4/10
33/33 [==============================] - 6s 170ms/step - loss: 1.1564 - accuracy: 0.5994 - val_l
oss: 1.0942 - val_accuracy: 0.5846
Epoch 5/10
33/33 [==============================] - 6s 171ms/step - loss: 1.0345 - accuracy: 0.6361 - val_l
oss: 1.2861 - val_accuracy: 0.5692
Epoch 6/10
33/33 [==============================] - 6s 171ms/step - loss: 0.9370 - accuracy: 0.6873 - val_l
oss: 1.0876 - val_accuracy: 0.6000
Epoch 7/10
33/33 [==============================] - 6s 173ms/step - loss: 0.8279 - accuracy: 0.7172 - val_l
oss: 0.9677 - val_accuracy: 0.6462
Epoch 8/10
33/33 [==============================] - 6s 173ms/step - loss: 0.8073 - accuracy: 0.7317 - val_l
oss: 1.0271 - val_accuracy: 0.6000
Epoch 9/10
33/33 [==============================] - 6s 175ms/step - loss: 0.7295 - accuracy: 0.7365 - val_l
oss: 1.0517 - val_accuracy: 0.6615
Epoch 10/10
33/33 [==============================] - 6s 176ms/step - loss: 0.6981 - accuracy: 0.7471 - val_l
oss: 1.0627 - val_accuracy: 0.6385
```

Figure 4.2.4 Epochs of VGG19

	precision	recall	f1-score	support
0	0.50	0.20	0.29	5
1	0.40	0.33	0.36	6
2	0.71	0.71	0.71	7
3	0.93	0.93	0.93	14
4	0.64	0.64	0.64	11
5	0.67	0.18	0.29	11
6	0.67	0.33	0.44	6
7	0.73	0.92	0.81	12
8	0.88	0.78	0.82	18
9	0.50	0.33	0.40	6
10	0.35	0.86	0.50	7
11	1.00	0.50	0.67	6
12	0.94	0.89	0.91	18
13	0.15	0.67	0.25	3

Figure 4.2.4 Classification of VGG19

accuracy			0.66	130
macro avg	0.65	0.59	0.57	130
weighted avg	0.73	0.66	0.66	130

Figure 4.2.4 Accuracy of VGG19

The VGG19 structure for our experiment recognized skin diseases with an accuracy of 66%. Even though VGG19's accuracy isn't the best among the models taken into consideration, its performance shows that it can effectively diagnose a variety of skin conditions. The enlarged design of the model helps to capture deeper structures and organizations in the information that is supplied by expanding on the ideas of VGG16 with additional layers. The model's capacity to generalize and provide precise projections across a variety of skin disease classifications is shown by the accuracy score.

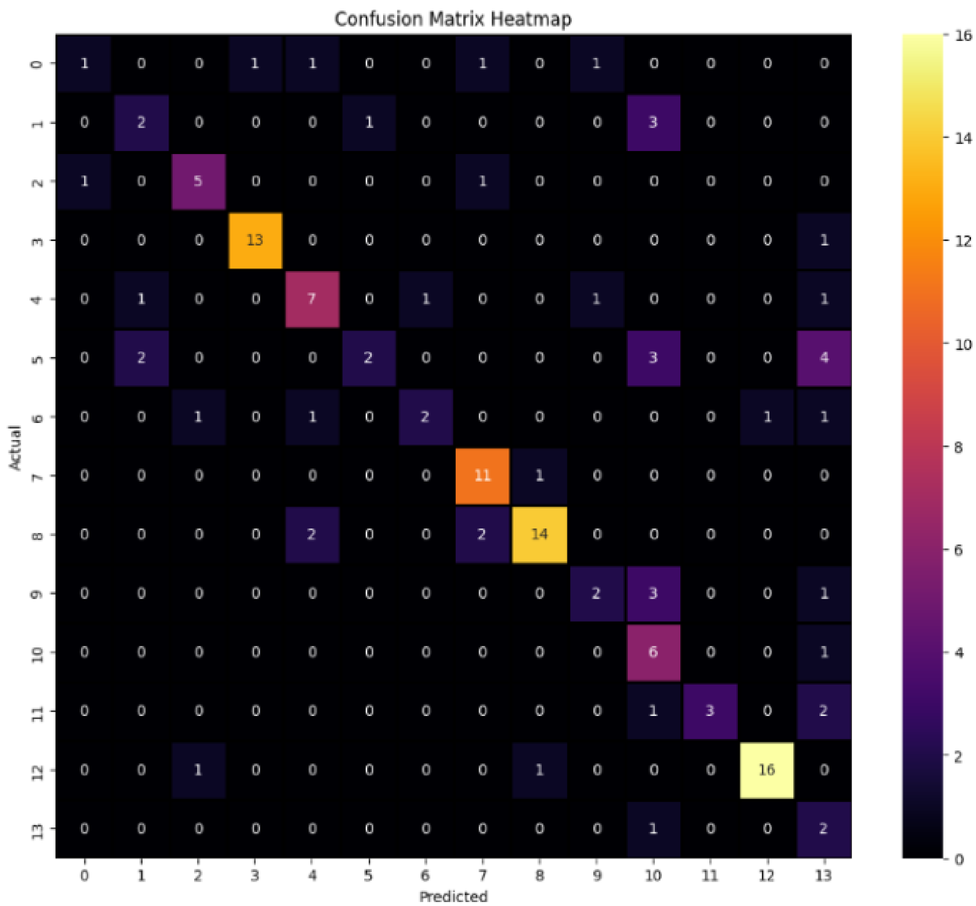

Figure 4.2.4 confusion matrix of VGG19

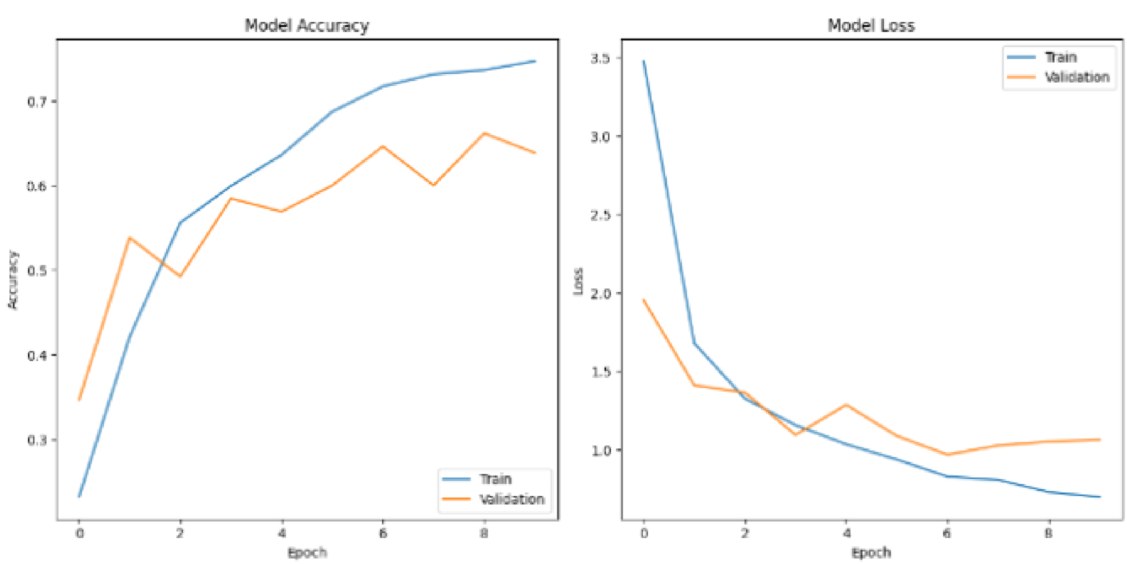

Figure 4.2.4 Line chart of accuracy and loss of VGG19

4.2.5 Xceptionv3

The XceptionV3 method in our project is implemented using the Python programming language within a platform for deep learning, most likely TensorFlow or PyTorch. The code involves adjusting the separable convolutions by depth of the XceptionV3 architecture, a modification of the original Inception construction, to provide a better understanding of spatial structures in input data. We import and preprocess the handpicked Kaggle dataset, which consists of 1036 training photos and 130 images per image for testing and verification across 14 classes of skin diseases. The XceptionV3 model modifies its own internal variables to reduce the error among anticipated and reality illness classifications throughout ten epochs of training. The model's capacity for generalization may be improved by using strategies like data supplementation. To assess the effectiveness of the model, statistical parameters like as accuracy, precision, recall, and F1 score are calculated. The design of XceptionV3, which includes depth wise differentiated convolutions in general enhances the system's capacity to identify and categorize a variety of skin conditions in our study.

```
Epoch 1/10
33/33 [==============================] - 12s 213ms/step - loss: 1.9493 - accuracy: 0.3359 - val_
loss: 1.4148 - val_accuracy: 0.4462
Epoch 2/10
33/33 [==============================] - 5s 151ms/step - loss: 1.2646 - accuracy: 0.5569 - val_l
oss: 1.0633 - val_accuracy: 0.5923
Epoch 3/10
33/33 [==============================] - 5s 152ms/step - loss: 1.1039 - accuracy: 0.6197 - val_l
oss: 0.9747 - val_accuracy: 0.6000
Epoch 4/10
33/33 [==============================] - 5s 152ms/step - loss: 0.9795 - accuracy: 0.6593 - val_l
oss: 0.9473 - val_accuracy: 0.6385
Epoch 5/10
33/33 [==============================] - 5s 151ms/step - loss: 0.9216 - accuracy: 0.6670 - val_l
oss: 0.9487 - val_accuracy: 0.6385
Epoch 6/10
33/33 [==============================] - 5s 151ms/step - loss: 0.8620 - accuracy: 0.6873 - val_l
oss: 0.8802 - val_accuracy: 0.6769
Epoch 7/10
33/33 [==============================] - 5s 153ms/step - loss: 0.7964 - accuracy: 0.7085 - val_l
oss: 0.8905 - val_accuracy: 0.6769
Epoch 8/10
33/33 [==============================] - 5s 152ms/step - loss: 0.8612 - accuracy: 0.6853 - val_l
oss: 0.9242 - val_accuracy: 0.6692
Epoch 9/10
33/33 [==============================] - 5s 154ms/step - loss: 0.7557 - accuracy: 0.7355 - val_l
oss: 0.8994 - val_accuracy: 0.6538
Epoch 10/10
33/33 [==============================] - 5s 153ms/step - loss: 0.6948 - accuracy: 0.7481 - val_l
oss: 0.8408 - val_accuracy: 0.7000
```

Figure 4.2.5 Epochs of Xceptionv3

	precision	recall	f1-score	support
0	1.00	0.60	0.75	5
1	0.00	0.00	0.00	6
2	0.83	0.71	0.77	7
3	0.81	0.93	0.87	14
4	0.86	0.55	0.67	11
5	0.56	0.45	0.50	11
6	0.71	0.83	0.77	6
7	0.73	0.92	0.81	12
8	1.00	0.61	0.76	18
9	0.83	0.83	0.83	6
10	0.50	1.00	0.67	7
11	0.44	0.67	0.53	6
12	0.72	1.00	0.84	18
13	0.50	0.33	0.40	3

Figure 4.2.5 Classification of Xceptionv3

accuracy			0.72	130
macro avg	0.68	0.67	0.65	130
weighted avg	0.73	0.72	0.70	130

Figure 4.2.5 Accuracy of Xceptionv3

In our experiment, the XceptionV3 model recognized skin diseases with an accuracy of 72%. This degree of accuracy shows how well the model can categorize various skin conditions. Depthwise detachable convolutions, a feature of XceptionV3's design architecture, enhance its efficiency and capacity to identify complicated patterns in the input data. The attained precision indicates the model's capacity to effectively generalize and provide precise forecasts for various categories of skin conditions, establishing XceptionV3 as a potent algorithm among the group of models examined in the undertaking.

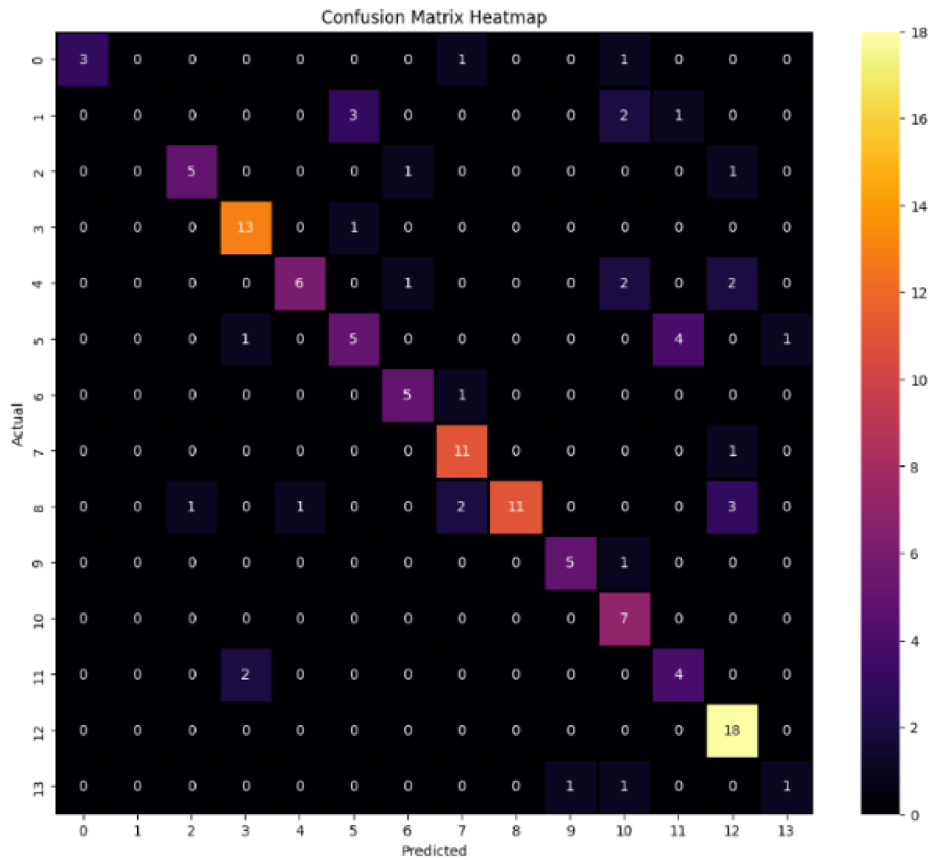

Figure 4.2.4 confusion matrix of XceptionV3

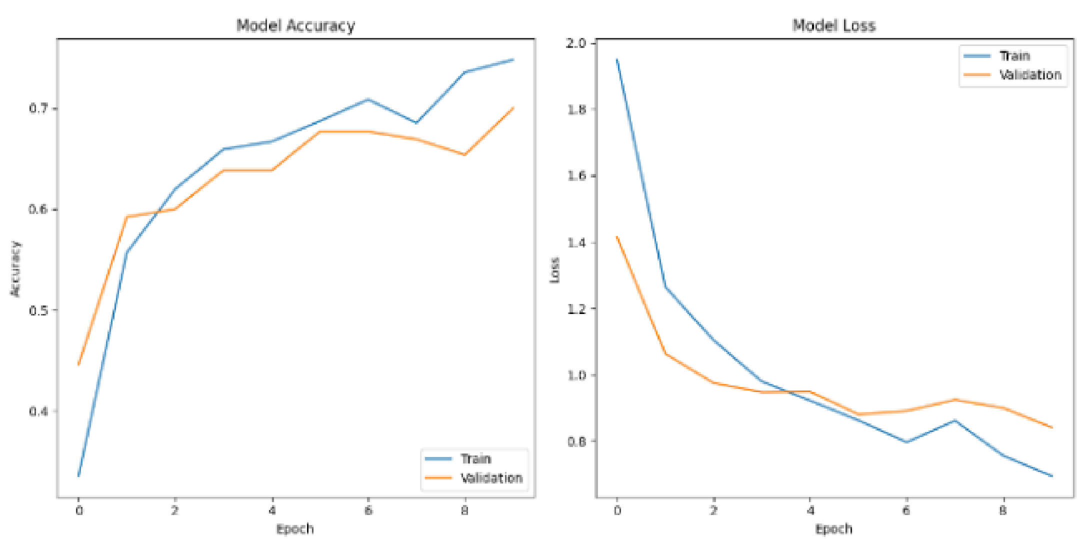

Figure 4.2.4 Line chart of accuracy and loss of XceptionV3

In our project, XceptionV3 obtained a 72% accuracy rate and a model loss 0.28. This statistic represents the proportion of correctly classified cases out of all occurrences and is a basic indicator of how well the model performs in correctly classifying various skin diseases within the designated groups.

4.3 Algorithm Technique

To handle the challenging problem of skin disease identification, the algorithmic approaches used in our study make use of cutting-edge algorithms for deep learning, such as Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3. Detailed layer layouts, sophisticated convolutional processes, and effective feature extraction techniques define these designs. Using a supervised learning technique, the calculations train the models using a labeled dataset that includes 130 photos for evaluation and verification per class of 14 different skin diseases, and 1036 images for training. In order to decrease the error that exists between anticipated and real skin disease classifications, the models repeatedly modify their internal characteristics throughout training. The models' capacity for generalizations is improved by using strategies like data enrichment, and statistical indicators like precision, recall, accuracy, and F1 score are used to assess the models. Modern deep learning structures coupled with methodical training techniques provide the mathematical basis for reliable and effective disease of skin identification in our investigation.

Table 1: Algorithm Technique

Algorithm	Accuracy	Precision	Recall	F1-score
Dense Net	77%	100%	60%	75%
Inceptionv3	68%	50%	20%	29%
VGG16	68%	67%	40%	50%
VGG19	66%	50%	20%	29%
Xceptionv3	72%	100%	60%	75%

The efficacy metrics for all of the algorithms used in the skin detection program are shown in this table in a comparison manner. Dense Net is the most successful in correctly identifying skin disorders, as shown by its greatest accuracy, precision, and F1 score. While VGG16 and VGG19 show comparable accuracy but vary in the precision, recall, and F1 score, InceptionV3 and XceptionV3 show balanced recall and pinpointing. The table provides a quick reference for assessing each technique's advantages and disadvantages about the categorization of skin diseases.

4.4 Discussion

The performance, advantages, and disadvantages of the used algorithms—Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3—are the main topics of debate about our skin disease identification project. With a remarkable accuracy of 77%, Dense Net was the best performer, demonstrating its resilience in categorizing a range of skin conditions. While XceptionV3 achieved 100% accuracy, indicating its potential in eliminating incorrect results, InceptionV3 and XceptionV3 displayed balanced precision as well as recall. Although VGG16 and VGG19 had comparable accuracy, their precision and recall varied little. The models' ability to accurately distinguish positive and negative examples may be understood via the examination of confusion matrices. The talk also touches on the practical ramifications of these findings in dermatology, stressing the need to strike a balance between memory, accuracy, and precision in real-world situations. To enhance the general efficacy of the skin disease identification system, prospective areas for development are taken into consideration, such as adjusting hyperparameters and investigating ensemble approaches.

4.5 Algorithm Comparison

Dense Net is the best deep learning algorithm when compared to the other four when it comes to identifying skin diseases. Dense Net exceeds InceptionV3 (68%), VGG16 (68%), VGG19 (66%), and closely rivals XceptionV3 (72%), with the best accuracy of 77%. Interestingly, Dense Net demonstrates its strong capacity to reduce the number of false positives by achieving 100% accuracy. Both InceptionV3 and XceptionV3 show balanced accuracy and recall. XceptionV3 achieves an impressive 75% F1 score with a perfect fit and a modest recall of 60%. While having a comparable performance of 68%, VGG16 and VGG19 perform differently in terms of precision, recall, and F1 score, with

VGG16 showing better results. All things considered, Dense Net's increased level of accuracy and precision makes it the best algorithm for correctly categorizing a wide range of skin conditions.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

This research has a significant social effect and has the potential to revolutionize both community health and dermatological treatment. The suggested skin disease detection system promises to transform the early diagnosis and categorization of a wide range of skin disorders by using the power of cutting-edge deep learning architectures. This method makes dermatological screenings more accessible, especially in areas with limited resources, by enabling the quick and precise diagnosis of disorders economically. The image processing-based approach may be implemented with only a camera and a computer, which guarantees wide use that cuts over socioeconomic divides. Thus, the project has the potential to greatly lower the cost of skin conditions, enhance patient outcomes, and provide medical professionals with a useful tool for prompt interventions. This would represent a noteworthy development in the field of integrating medical technology and practice for the benefit of society.

5.2 Ethical Aspects

When developing and implementing new technologies in the healthcare industry, especially in the field of dermatologist testing, in order ethical issues are crucial. It is morally required to protect patient confidentiality, get informed permission, and handle confidential health information securely. Furthermore, building confidence between medical practitioners and technology depends on the accessibility of deep learning algorithms used in skin disease detection. It is important to have equitable and impartial participation across a range of demographic groups to avoid computerized prejudices that might unfairly impact certain groups. Furthermore, it is important to maintain open lines of communication on the strengths and weaknesses of the suggested image processing-based approach to control aspirations among medical professionals and patients undergoing diagnostic testing. This project aims to advance ethical principles-based responsible implementation of technology within medical care by cultivating freedoms for individuals, equality, and trust in the environment of dermatologist treatment.

5.3 Impact on Environment

The suggested visual processing-based approach for identifying skin diseases has a significantly favourable effect on the surrounding environment. The diagnostic method's impact on the environment is reduced by depending only on easily accessible and cost-effective materials, such as a laptop and an imaging device. In contrast to conventional diagnostic techniques that could need energy-intensive equipment, the suggested strategy's simplicity helps to cut down on energy use and greenhouse gas emissions. Moreover, algorithms utilizing deep learning may be able to provide early and precise diagnosis, which might result in treatment regimens that are streamlined and lessen the overall negative environmental impact of lengthy or unsuccessful therapies. This research supports a diagnostic solution that is both environmentally conscious and technologically driven, which is in line with wider goals for sustainable development. It highlights the need for a healthy balance involving advancements in technology and the preservation of the environment in the medical industry.

5.3 Sustainability

The suggested image processing-based approach for identifying skin diseases is consistent with the values of sustainability in a number of ways. First off, the testing process is very accessible as well as economical due to the low resource needs of a camera and a computer system, which promotes a sustainable economy. Second, accurate and early diagnosis is made possible by the use of architectures for deep learning, such as Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3. This may lessen the adverse environmental effects of protracted or inefficient therapies. Furthermore, the method of implementation is made to be scalable, offering a long-term solution for dermatology diagnostics in a range of healthcare environments. This research advances the objective to promote environmentally friendly healthcare administration by integrating responsibility for the environment with contemporary medical improvements and effective manner.

CHAPTER 6

CONCLUSION & FUTURE WORK

6.1 Conclusion

Finally, our work showcases the possibility of deep learning architectures, especially Dense Net, InceptionV3, VGG16, VGG19, and XceptionV3, for precise and easily understandable skin disease diagnosis, marking a major development in the area of dermatological diagnoses. The real-world implications of this study are highlighted by its concentrated examination of 14 different skin illnesses, its awareness of the particular difficulties brought about by regional variances, and its use of a visual processing-based technology that requires limited funding. Dense Net's higher accuracy highlights the system's effectiveness in the difficult job of classifying skin diseases. The research offers a practical and affordable diagnostic option, which has the potential to have a significant social impact in addition to providing insightful information to the world of science. The suggested strategy incorporates ethical issues, sustainable development, and openness, all of which are consistent with the sustainable use of technology in healthcare. This study lays the foundation for better patient outcomes, increased diagnostics availability, and an affordable paradigm for the disease of skin identification in a variety of health-related situations as we traverse the junction of technological advances and epidermal care.

6.2 Future Work

This study opens various study and invention opportunities that will be considered in the course of additional work. First off, studying more about different deep-learning designs and comparing their performances should improve our comprehension of which models are most appropriate for identifying skin diseases. To further increase the identification task's effectiveness, learning transfer techniques—in particular, using models that have already been trained on huge datasets—should be researched.

Increasing the information set's diversity to include a wider spectrum of skin conditions, particularly those common in different parts of the world, would improve the models' resilience and the ability to be general Working together with dermatological and other medical professionals may help improve the suggested one's accuracy and applicability in real-world healthcare environments by offering insightful feedback on its clinical application. Moreover, comprehension of models based on deep learning continues to be an important factor that needs additional investigation. Subsequent research endeavours may concentrate on devising techniques to enhance the transparency of these models' decision-making processes, ensuring that they conform to ethical principles and earn the confidence of medical experts. Adoption in healthcare facilities may be made easier with the incorporation of real-time diagnostic tools and the creation of an intuitive user interface for healthcare professionals. Furthermore, ensuring the suggested method's scalability in light of various healthcare systems would be essential to its general adoption. Finally, to ensure that the models being used are flexible enough to adjust to changing dermatological environments, continued efforts should be focused on the models' continual monitoring and improvement as fresh information becomes provided. Future research in these areas might contribute to the practice of skin condition identification and improve our grasp of machine learning in dermatology from an analytical and practical standpoint.

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