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HYBRID DEEP LEARNING MODELS FOR MULTI-CLASS SKIN DISEASE CLASSIFICATION

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ABSTRACT

The aim of this study is to test deep-learning models that can identify different types of skin diseases. This study examines illnesses caused by tiny living things, like germs and parasites. The information used in this study came from Kaggle and included pictures of eight types of skin diseases. These pictures were changed by resizing them, changing their colors, and adding different types to make them look better. The information was split into 80% for training and 20% for testing. Five models—CNN, SVM, ResNet50, VGG16, and Mobile-Net—were created and tested using common measures like precision, accuracy, recall, and F1-score. Transfer learning was used with pre-trained deep learning models (ResNet50, VGG16, and Mobile-Net) to make them perform better on this specific dataset. The test showed that VGG16 and Mobile-Net performed much better than the other models, with both achieving 98% accuracy. VGG16's deeper design helped it find details accurately, while Mobile-Net's simpler design kept it fast without losing accuracy. ResNet-50 achieved 96% accuracy, showing that it is good at handling complex patterns. CNN and SVM performed well, achieving accuracy rates of 94% and 93%.

Keywords: *Convolutional Neural Networks (CNN), Deep learning, Medical image processing, and Skin disease types,*

1. INTRODUCTION

Skin issues, particularly those caused by modest germs, contaminations, and parasites, are a few of the greatest well-being issues in the world (Debelee, 2023). These conditions, extending from mellow contaminations like impetigo to more genuine ones like cellulitis, can incredibly influence a person's well-being and quality of life on the off chance that they are not analyzed and treated rapidly (Sun et al., 2023). Knowing precisely what is off-base is vital to maintaining a strategic distance from issues afterward. In any case, standard testing strategies frequently have issues, like depending on doctors' involvement, having few devices accessible, and confronting asset confinements, particularly in less-created zones (Hatem & Art, 2022). In this circumstance, computerized symptomatic frameworks fueled by machine learning, particularly profound learning models, have extraordinary potential to make strides in the speed and precision of analysis while overcoming conventional impediments (Kalaivani & Karpagavalli, 2022). In later a long time, convolutional neural systems (CNNs) have been effective devices for classifying restorative pictures and counting distinguishing skin infections (Gallardo, Arboleda, Dones, Panganiban, & Technology, 2024). These frameworks can learn imperative highlights from pictures and tell the distinction between different sorts of diseases based on designs within the information. Indeed so, there are still issues to confront despite their win (Saiwaeo, Arwatchananukul, Mungmai, Preedalikit, & Aunsri, 2023). Skin illnesses frequently seem comparable to each other, and the accessible information for preparing is frequently uneven, with a few illnesses not having sufficient illustrations. This creates issues for normal CNNs and machine learning models, which might battle to perform well in real-life circumstances (Pitchiah & Rajamanickam, 2022).

To unravel these issues, modern progressed learning models have been recommended. These models blend diverse machine learning strategies to move forward execution (Yadav, Bhat, & Applications, 2024). This consideration looks at five diverse models for classifying different sorts of skin illnesses: Convolutional Neural Systems (CNN), Bolster Vector Machine (SVM), Mobile-Net, ResNet50, and VGG16. Each of these models was picked since they have demonstrated to work well for restoring pictures and can oversee complicated information. Employing a combination of diverse models can offer assistance in making strides in the accuracy of classification by taking advantage of the qualities of each demonstration (Kanca & Ayas, 2022). This will lead to way better locations of maladies that have unpretentious contrasts in their appearance (Nalamwar & Neduncheliyan, 2023).

This ponder contains pictures of eight diverse sorts of skin diseases, assembled into four fundamental categories: bacterial diseases (like cellulitis and impetigo), parasitic diseases (like athlete's foot, nail organism, and ringworm), parasitic contaminations (like cutaneous hatchling migrans), and viral diseases (like chickenpox and shingles). These ailments have a extend of indications, from redness and swelling in bacterial diseases to broad rashes and tingling in viral diseases. The objective is to test the chosen models on this dataset to see how well they can precisely distinguish distinctive illnesses utilizing as it were pictures (Kalpana, Reshmy, Pandi, Dhanasekaran, & Control, 2023). Profound learning models, particularly ones like Mobile-Net, ResNet50, and VGG16, have appeared they handle huge sets of pictures exceptionally well. Mobile-Net is awesome since it employments less computing control, making it a great choice for places with constrained assets, like country clinics. On the other hand, ResNet50 has profound layers that offer assistance in getting complicated subtle elements in complex pictures. VGG16, even though it requires more computer control, has reliably done awesome work in restorative imaging errands since it can keep in mind nitty-gritty levels of picture highlights (Aswath, Kalaiyarivu Cholan, & MISS, 2022). On the side of these profound learning models, conventional machine learning methods like Bolster Vector Machines (SVM) are too included within the think about. SVMs are great at working with little datasets and circumstances where distinctive bunches may cover (Saraphon, Chaising, Aung, & Srimaharaj, 2024). This makes them valuable when there are many visual similarities between illnesses. This consideration looks at how these models work to discover the perfect way the most perfect way to classify skin infections. The point is to move forward with robotized demonstrative apparatuses (Saeed, Naseer, Masood, Rehman, & Gruhn, 2023).

The findings from this research will be very important for improving how accurately skin conditions are diagnosed, especially in areas where there aren't many expert skin doctors available (Indriyani, Ida, Made, Made, & Applications, 2023). Computer systems using these mixed models can quickly and accurately find skin diseases. This helps healthcare providers make timely treatment decisions. Also, by reducing the pressure on healthcare systems and lowering the need for costly tests, these models can help make healthcare easier for people everywhere (Banditsingha, Thaipisutikul, Shih, & Lin, 2022). This survey examines various deep-learning models used to classify different types of skin diseases. This won't just show the potential of deep learning in medical diagnosis, but it will also lead to future research into more advanced diagnostic systems (Kara, Kara, & Çelik, 2023). This asks about ways to improve the accuracy and efficiency of diagnosing skin infections. It could greatly benefit healthcare around the world, especially in areas with limited access to regular diagnostic tools (Kara et al., 2023).

2. LITERATURE REVIEW

Recent advancements in identifying skin conditions from damaged images have improved a lot because of the use of machine learning and deep learning techniques. This audit focuses on specific methods for classifying skin diseases and discusses what they do well and what their limits are. (Hoang, Lee, Lee, & Kwon, 2022) they created a computer tool for taking special pictures called epi-illumination (ELM) and trans illumination (TLM) using methods like K-means clustering, wavelet analysis, and shape operations. They used a Back Vector Machine (SVM) to sort data, achieving a high accuracy of 81. 0% for one measure and 90. 4% for another Even though this guide shows a basic way to handle injuries, its use of traditional machine learning methods and manual adjustments makes it less flexible and harder to adapt to different datasets and real-life situations (Sujatha, Lavanya, Niveditha, & Saranya, 2024). I'm sorry, but "Litjens et al. " appears to refer to a citation or a group of authors and does not contain enough context or information (Karthik et al., 2022). Could you please provide more details or some text you'd like to have rewritten? They looked at how critical learning can help with analyzing images, focusing on tasks like separating images, getting important details, and sorting them (Senthilselvi, 2023). They considered expanding areas of study like brain science, eye medicine, and disease research, showing the promise of significant improvements in diagnosis accuracy. However, using these models on skin images is tricky because the skin can look different depending on the lighting and other conditions, which can impact how well the model works and how useful it is in general (Kalbande, Dhamane, & Bhope, 2024).

(Keerthana, Venugopal, Nath, & Mishra, 2023) proposed a cross-breed framework combining Convolutional Neural Frameworks (CNNs) with SVMs for melanoma areas. This approach pointed to utilizing the qualities of both significant learning and ordinary machine learning methodologies to advance division and classification accuracy (Chyad et al., 2024). In showing disdain toward finishing striking comes around, the crossbreed appears gone up against challenges related to manual parameter tuning and tall computational demands, which can influence its practical fittingness and viability in clinical settings. (Bhosale, 2022) displayed a dual-method approach for skin tumor classification, utilizing pre-trained CNNs in combination with K-Nearest Neighbors (KNN) and AlexNet optimized with the Gray Wolf calculation. The combination of these methodologies finished tall classification precision, but the models combat with generalization over grouped datasets, highlighting the dependence on the quality and changeability of planning data. This obstruction underscores the require for models that can alter to a more broad amplification of skin conditions and picture qualities. (Zhang et al., 2023) made a bioinspired significant learning illustration that plans clinical components with picture examination for skin sickness assurance. This appears to utilize Elephant Swarm Optimization (EHO) and Antlion Optimization (ALO) to update accuracy and unflinching quality (Zhang et al., 2023). While the integration of clinical data and optimization techniques given promising comes around, the model's complexity and tall computational necessities posed basic challenges. Too, the model's dependence on correct and comprehensive tireless data may compel its generalizability and practical utilization (Agarwal, Godavarthi, & Technology, 2023).

(Hsu, Tseng, & biomedicine, 2022) proposed a novel method for skin ailment disclosure utilizing non-dermoscopic camera pictures captured from various focuses. Their approach, based on DeepLabv3 for division, pointed to making a comprehensive dataset for classifying distinctive skin diseases (Oliveira, Ferreira, Azevedo, & Almeida, 2023). In showing disdain toward the truth that this methodology outlined practicality in segmenting skin and wound locale, the reliance on non-standard pictures results in poorer execution compared to dermoscopic image-based models. Inconstancy in picture quality and lighting conditions' progress complicated the model's precision, highlighting the limitations of utilizing non-standard imaging methods for skin ailment assurance.(Singh, Verma, & Ranvijay, 2023) utilized machine learning calculations, tallying Back Vector Machines (SVMs), and choice trees, to classify skin conditions based on surface and color highlights removed from pictures (Xiang & Chen, 2022). The utilization of histogram estimations, such as tint, submersion, and regard (HSV), enabled compelling texture-based classification (Wang et al., 2023). In any case, the method's reliance on physically removed highlights and compelled generalization to arranged skin surfaces and conditions posed challenges (KARA ARDAÇ, KARA, Çelik, & Technology, 2023). The model's execution was closely tied to the exactness of highlight extraction, which can move inside and out over assorted picture datasets (Xin et al., 2022).

(Pashkovska & Nursing, 2024) displayed a neural network-based illustration that combined multimodal information from skin ailment pictures and restorative metadata. They appear to utilize a Vision Transformer (ViT) for picture examination and a Sensitive Tag Encoder (SLE) for dealing with metadata (Zia Ur Rehman et al., 2022). The joining of common thought squares pointed to the progress in the integration of picture highlights and metadata, promoting a more comprehensive approach to skin disease classification (Charulatha, Dineskkumar, Kaleeswari, Lakshmipriya, & Research, 2023). In showing disdain toward its creative arrangement, the appears to stand up to challenges related to the complexity of coordinating multimodal data and the computational resources required for dealing with it (Aldhyani, Verma, Al-Adhaileh, & Koundal, 2022).

A study of these considers reveals a couple of gaps and challenges inside the current approaches to skin disease classification. Various existing models either depend on escalation on pre-trained frameworks or utilize complex cross-breed techniques that ask for noteworthy computational resources and manual optimization. Besides, the execution of these models as often as possible depends on the quality and changeability of the planning datasets, obliging their generalizability and down-to-soil relevance. They appear to consider addressing these gaps by proposing a cross-breed significant learning that plans Convolutional Neural Frameworks (CNN), Back Vector Machines (SVM), MobileNet, ResNet50, and VGG16 structures for multi-class skin ailment classification. This appears focuses to optimize computational capability while keeping up tall classification precision over a grouped amplify of skin conditions. By solidifying advanced picture pre-processing and division methods, the proposed illustration overcomes the obstacles of manual highlight extraction and wide parameter tuning. This approach offers a flexible, solid course of action for skin sickness classification, with the potential for broader clinical application and moved forward illustrative precision over varying picture sorts and illness categories.

3. METHODOLOGY

This think about looks closely at the issues of finding skin infections utilizing profound learning strategies. The method has key steps: collecting data, settling any blunders, making the show, instructing it, and checking how well it performs. This considers employment information from Kaggle, which incorporates different pictures of skin maladies caused by microbes, parasites, parasites, and infections. This strategy points to constructing and testing compelling models for precisely recognizing skin maladies. In this think about, five diverse models are utilized to classify skin illnesses: Convolutional Neural Systems (CNN), Bolster Vector Machines (SVM), ResNet50, VGG16, and MobileNet. The dataset comes from Kaggle and has pictures of distinctive skin maladies, counting contaminations caused by microbes, organisms, parasites, and infections. The information is part into two parts: 80% is utilized to prepare the models, and 20% is utilized to test how well they work. This division makes beyond any doubt there's sufficient data for making and checking the show.

3.1 Dataset Description

The dataset from Kaggle consists of images categorized into the following classes:

1. Bacterial Infections - cellulitis
2. Bacterial Infections - impetigo
3. Fungal Infections - athlete's foot
4. Fungal Infections - nail fungus
5. Fungal Infections - ringworm
6. Parasitic Infections - cutaneous larva migrans
7. Viral Skin Infections - chickenpox
8. Viral Skin Infections – shingles

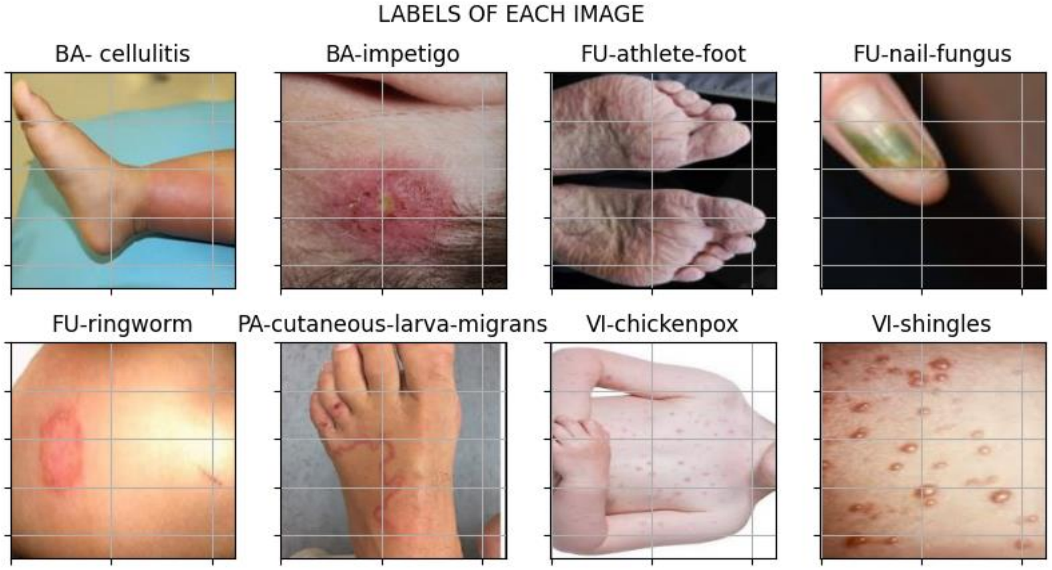


Figure:1 Classes within Dataset

The dataset utilized in this think about was sourced from Kaggle, comprising pictures categorized into eight classes of skin infections: cellulitis, impetigo, athlete's foot, nail organism, ringworm, cutaneous hatchling migrans, chickenpox, and shingles. The pictures were preprocessed by resizing them to 224x224 pixels with three color channels (RGB), which is standard for profound learning models. The information was part of preparing (740 pictures), approval (185 pictures), and testing sets (925 pictures), with one-hot encoding connected to the names for multi-class classification. To improve the model's capacity to generalize, information expansion methods like level flipping, turn, and zooming were utilized. The pixel values were normalized to a run of to 1, speeding up the show meeting. This cautious preprocessing guaranteed the dataset was well-suited for profound learning applications, contributing to more precise and dependable demonstration execution.

3.2 Data Preprocessing

3.2.1. Image Resizing and Normalization: -

To guarantee consistency over the dataset, all pictures are resized to a uniform measurement of 214x214 pixels (Chandragiri et al., 2024). This step makes a difference in lessening computational complexity and keeping up consistency. Moreover, pixel values are normalized to an extent of [0, 1] to encourage speedier meetings amid show preparation.

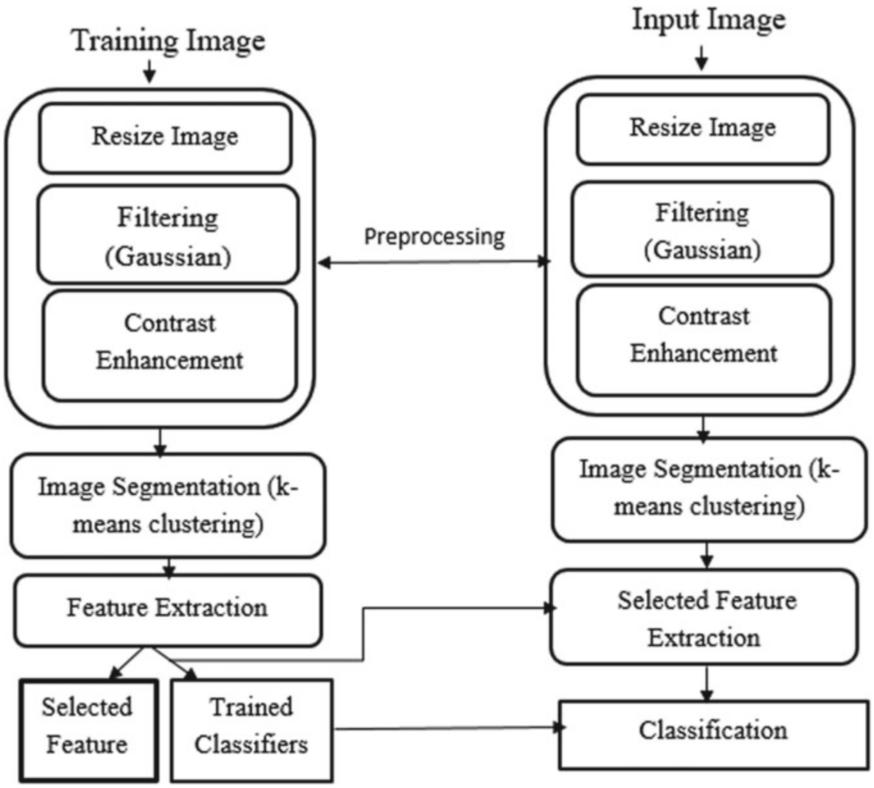


Figure: 2: - The structure of the suggested system

3.2.2. Data Augmentation: -

Since there may be a lopsidedness within the number of illustrations for each course, and to make the demonstration more grounded, we utilize information enlargement methods (Nguyen, Bui, & Do, 2022). These strategies include turning pictures with completely different headings, flipping them sideways and up and down, zooming in and out, and moving them around a bit (Sahu, Shrivas, & Shukla, 2023). An increase makes a difference and makes a more changed set of information, which is imperative for progressing how well a demonstration works on unused data and avoiding it from getting as well centered on fair the preparing information.

3.3 Model Development: -

3.3.1. Architecture Selection:

A few convolutional neural arrange (CNN) models are considered for this consideration, counting VGG16, ResNet50, MobileNet, and SVM. Each show is chosen based on its execution in earlier times and its reasonableness for the classification errand at hand.

3.3.2. Convolutional Neural Network (CNN): -

This type of computer program designed to recognize patterns in pictures and videos. CNNs are strong deep-learning tools that work well for sorting images because they automatically learn different levels of features using their special layers (Malo, Rahman, Mahbub, & Khan, 2022). In this study, we use a CNN model as a starting point. It begins with convolutional layers that pick out important details like edges and textures from the images we input. After the convolutional layers, there are pooling layers that make the size of the data smaller while keeping important details. Finally, fully connected layers put together the features to predict the disease type for each image. CNN can spot complicated patterns in pictures, making it great for classifying skin diseases. The system automatically changes the settings to improve its accuracy during training over several rounds. Recent studies show that CNNs are good at classifying skin conditions because they can see and understand fine details in different ways.

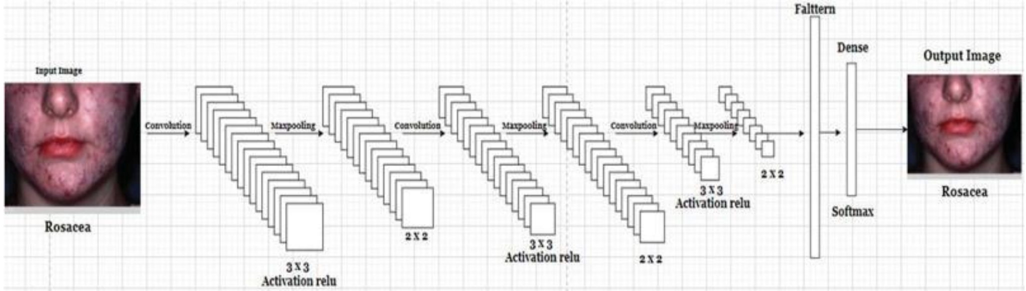
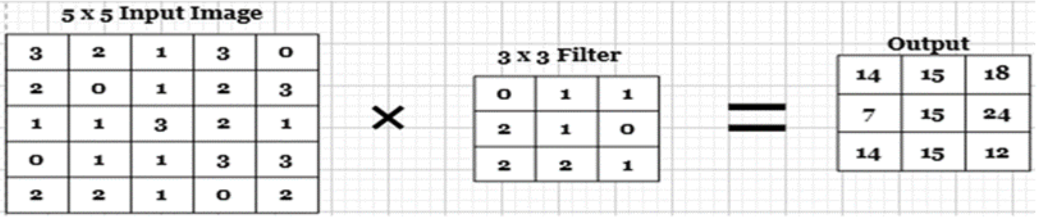


Figure: 3. Convolutional neural network (CNN) model flow used in this research with 13 layers.



$$\begin{bmatrix} 3 & 2 & 1 & 3 & 0 \\ 2 & 0 & 1 & 2 & 3 \\ 1 & 1 & 3 & 2 & 1 \\ 0 & 1 & 1 & 3 & 3 \\ 2 & 2 & 1 & 0 & 2 \end{bmatrix} \times \begin{bmatrix} 0 & 1 & 1 \\ 2 & 1 & 0 \\ 2 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 14 & 15 & 18 \\ 7 & 15 & 24 \\ 14 & 15 & 12 \end{bmatrix}$$

$$(3x0) + (2x1) + (1x1) + (2x2) + (0x1) + (1x0) + (2x1) + (3x1) = 14$$

Figure: 4: - Example of input image filtered by using con2d with a 3 × 3 kernel

In this, the input image is called i, the image filter is called f, and m and n represent the number of rows and columns of the kernels. Images have important details that are taken out using small grids called kernels. Convolution is a way of using these grids in a two-dimensional way to see how much the image matches with various filters (Surendren & Sumitha, 2023).

$$z[m, n] = (i * f)[m, n]$$

This means that the value of z at position (m, n) is equal to the value of i times the value of f at the same position (m, n). The input image is a square grid of size n × n, and the filtered image is a smaller square grid of size m × m. The output size will be (n - m + 1) × (n - m + 1). Figure 6 shows this process, where the values move one column to the right each time and slide down one row at a time. This is called striding, shown as stride = k. The result can be written as ([n - m]/k + 1) times ([n - m]/k + 1).Using strides with the 3 × 3 matrix makes the output smaller, so we can keep the same input image size, which is a 5 × 5 matrix. The padding adds zeros around the edges of an image to make it the same size as the original input (Galagali).

3.3.3. Support Vector Machine (SVM): -

It is a type of computer program used for finding patterns in data and making decisions or predictions (Kumar et al., 2023). It works by drawing a line (or a boundary) that best separates different groups in the data. SVM is an older machine learning method mainly used to sort things into different groups. Unlike deep learning models, SVM is simpler and doesn't have many layers. Instead, it works by finding the best line (or hyperplane) that divides different classes (Thanh, Nguyen, & Applications, 2024). In this study, we use a method called one-vs-rest to improve SVM for classifying multiple categories. The model changes the image data into simple lists of features, and then the SVM algorithm finds a line that best separates the different types of skin diseases. SVM usually works well when there are clear differences between groups. However, its success with image tasks, especially in medicine, relies a lot on how well the important details are captured from the images.

3.3.4.ResNet50: -

This type of computer program that helps computers understand images. It has 50 layers, which means it looks at pictures in many steps to understand them much better (Nirmala, Shashank, Manoj, Satish, & Premaladha, 2023). ResNet50 is a type of deep learning model that helps solve a problem known as the vanishing gradient problem. It uses special links called residual connections, which allow information to flow easily through the network, even when it is very deep (Zhu et al., 2024). The show has 50 layers, and each part has different paths that go around some of the layers. This plan helps show how to learn complex designs without dealing with problems that often arise in deeper systems (Omeroglu, Mohammed, Oral, & Aydin, 2023). In this study, ResNet50 analyzes pictures of skin diseases and learns patterns using special parts called residual blocks. The show starts by pointing out important small things like lines and surfaces. As it goes deeper, it learns to see more complicated patterns that help identify different skin problems. ResNet50 has done very well at identifying medical images because it can handle the deep and complex details needed to find important features in these pictures.

3.3.5. VGG16: -

This type of computer program utilized in picture acknowledgment. It makes a difference computer gets it and identifies(B. V. Reddy et al., 2023) different objects in pictures. VGG16 could be a sort of profound learning show with 16 layers (Nancy). It is straightforward and works well. The show plan employments little 3x3 channels and has more layers to steadily get it more complex highlights. In this consideration, we utilize VGG16 to see how its more profound structure can offer assistance in classifying skin infections as superior (H. T. Nguyen et al., 2022). The organization recognizes diverse levels of points of interest, beginning with basic designs and moving to more complex ones (Rangkuti & Hasbi, 2023). This makes a difference in recognizing diverse sorts of skin illnesses more viably. Later it appeared that VGG16 works well in analyzing therapeutic pictures. Its profound structure makes a difference it precisely classifies pictures that are seen as comparative.

3.3.6. Mobile-Net: -

This could be a sort of computer program utilized for recognizing pictures or objects in pictures. It's planned to work well on versatile gadgets, like smartphones, so it can run quickly and utilize less battery (B. V. Reddy et al., 2023). Mobile-Net may be a little deep-learning show outlined to work well on portable gadgets and in places with small computer controls. Mobile-Net employments a method called depth-wise distinct convolutions (SM, P, Aravindan, Appavu, & Applications, 2023). This makes a difference in lowering the number of parameters required while still keeping great execution (Corbin, Marques, & Applications, 2023). In this consideration, Mobile-Net is utilized to see how well it can identify skin infections rapidly. It begins by breaking the picture into distinctive parts employing a strategy called depth-wise convolution. This strategy brings down the computing costs, making a difference the demonstrate to handle pictures quicker while still being exceptionally precise (A. H. K. Reddy & Vidhya, 2022). Mobile-Net works well, which makes it extraordinary for therapeutic employments that require speedy comes about.

3.4 Model Steps and Checking Result: -

The dataset is part of 80% for preparation and 20% for testing for all models. Within the preparation stage, we donate 80% of the information to each show so they can learn to recognize the distinctive skin maladies (Sadik, Majumder, Biswas, Ahammad, & Rahman, 2023). In this organization, we alter settings like learning rate, bunch estimate, and the number of times the demonstration goes through the information to make it work way better. The testing stage implies checking how well the prepared models work with the final 20% of the information. This makes a difference to form beyond any doubt they can handle unused, inconspicuous information viably. Each demonstration is measured utilizing common apparatuses, such as precision, exactness, review, and F1 score. These numbers show how great each demonstration is at recognizing skin infections. They come about will compare standard strategies and profound learning strategies to determine which one is superior for classifying skin maladies. In brief, these models utilize a great combination of conventional and progressed learning strategies. They go from fundamental highlight extraction in SVM to more complicated profound learning in CNN, ResNet50, VGG16, and Mobile Net. They work together to illuminate the issue of classifying distinctive sorts of skin illnesses.

3.4.1. Transfer Learning: -

To leverage the pre-trained knowledge of these models, transfer learning is employed. Pre-trained weights from models trained on ImageNet are used as starting points. This approach reduces the need for extensive training from scratch and improves model performance on the skin disease classification task.

3.5 Model Training and Validation: -

3.5.1. Training: -

The selected models are fine-tuned on the skin disease dataset using a training-validation split. A typical split of 80% for training and 20% for validation is employed. During training, a batch size of 32 is used, and the models are trained for 20,50 and 100 epochs with early stopping to prevent over fitting.

3.5.2. Hyperparameter Tuning: -

Hyperparameters such as learning rate, batch size, and optimizer type (e.g., Adam, SGD) are optimized through grid search and cross-validation techniques. This process ensures that the models are trained with the most effective settings.

3.5.3. Evaluation Metrics: -

The performance of the trained models is evaluated using several metrics to ensure a comprehensive assessment:

- ***Accuracy:*** The ratio of correctly predicted instances to the total number of instances.
- ***Precision, Recall, and F1 Score:*** These measurements are especially useful for uneven datasets, helping us understand how well the model does for each group.
- ***Confusion Matrix:*** A detailed matrix is generated to visualize the model's classification performance across different skin disease classes.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F_1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Figure-5: - Performance Metrics Formulas

They all focus on how a model learns to tell apart a specific group we care about (positive group) from everything else (negative group). The model can be corrected in two ways:

- ***True Positive ("TP"):*** The model correctly finds data that belongs to the positive group.
- ***True Negative (TN):*** the model accurately recognizes data that belongs to the negative group.

The model can be wrong in two ways:

- ***False Positive (FP):*** The model wrongly marks data that is negative as positive.
- ***False Negative (FN):*** the model mistakenly marks positive items as negative.

3.6 Post Processing: -

To enhance the interpretability and usability of the model predictions, post-processing steps are applied. These include:

- ***Probability Threshold Adjustment:*** Adjusting the cutoff point for deciding if images belong to a certain category so that we can improve both the accuracy of the results and the number of correct identifications.
- ***Visualization of Results:*** Creating visual tools like heatmaps to show where the model paying attention and to help understand the classification results better.

3.7 Comparison with Existing Methods: -

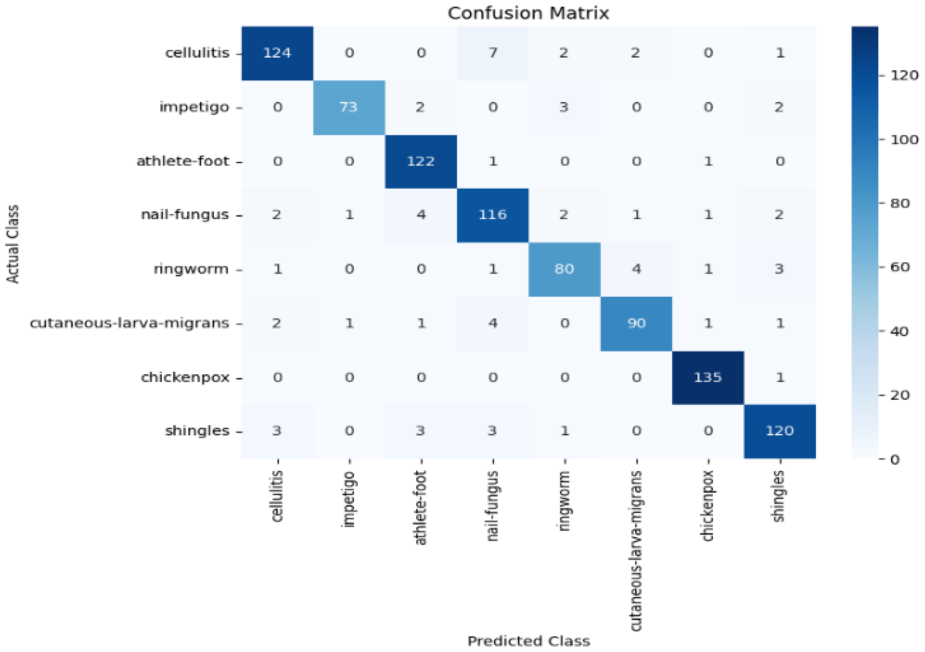
To check if the new method works well, we compare the performance of the models we created with other methods already written about. This comparison looks at measures like how accurate the models are and their F1 scores using different methods and models.

3.8 Summary

This method gives a clear way to create and assess deep-learning models that classify skin diseases. The study wants to accurately identify and classify different skin diseases by using advanced CNN models, transferring knowledge from other models, and applying careful data preparation methods. The thorough review and comparison with other methods show that this new approach fixes the problems found in earlier studies, providing useful information for skin disease diagnosis.

4. RESULTS: -

4.1 CNN Model: -



	cellulitis	impetigo	athlete-foot	nail-fungus	ringworm	cutaneous-larva-migrans	chickenpox	shingles
cellulitis	124	0	0	7	2	2	0	1
impetigo	0	73	2	0	3	0	0	2
athlete-foot	0	0	122	1	0	0	1	0
nail-fungus	2	1	4	116	2	1	1	2
ringworm	1	0	0	1	80	4	1	3
cutaneous-larva-migrans	2	1	1	4	0	90	1	1
chickenpox	0	0	0	0	0	0	135	1
shingles	3	0	3	3	1	0	0	120

Figure-6: - Confusion Matrix with CNN Model

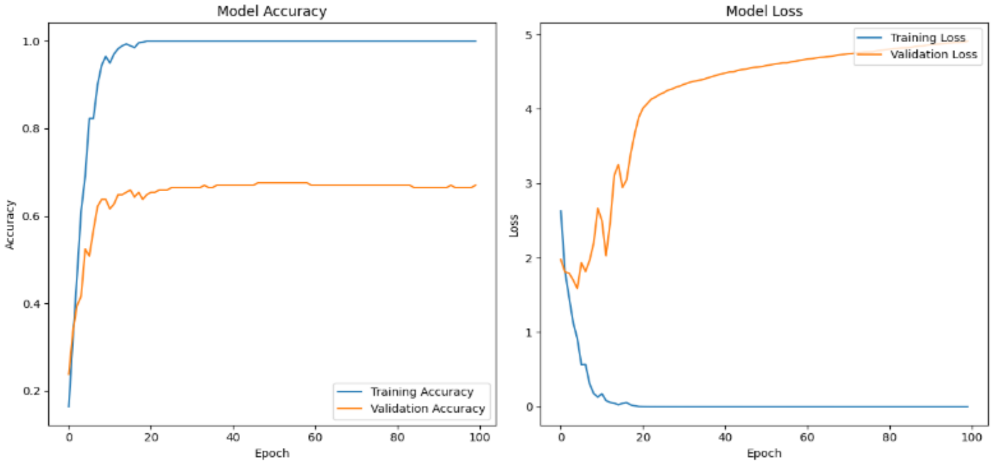
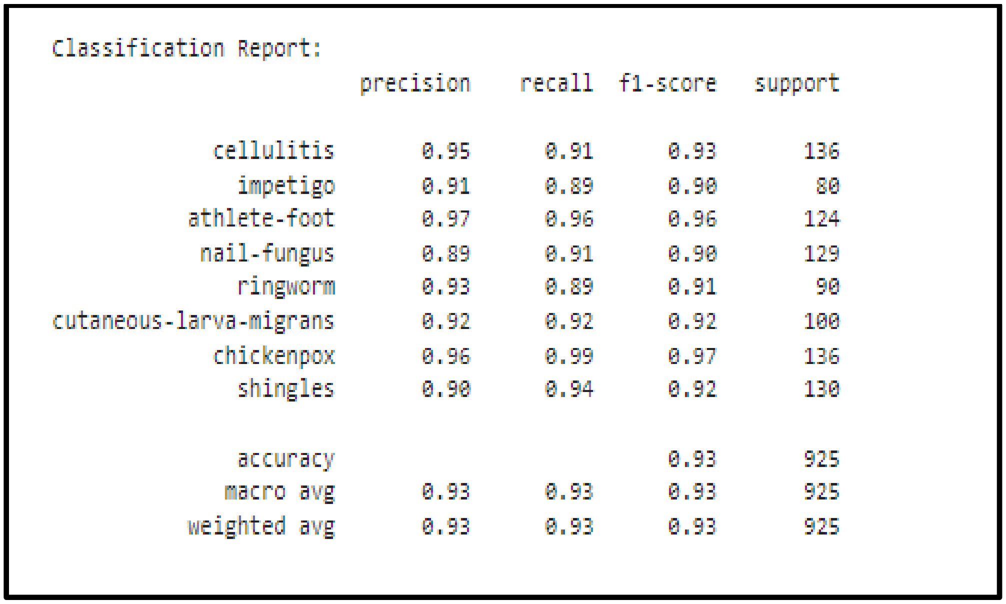


Figure-7: - CNN Model Plots

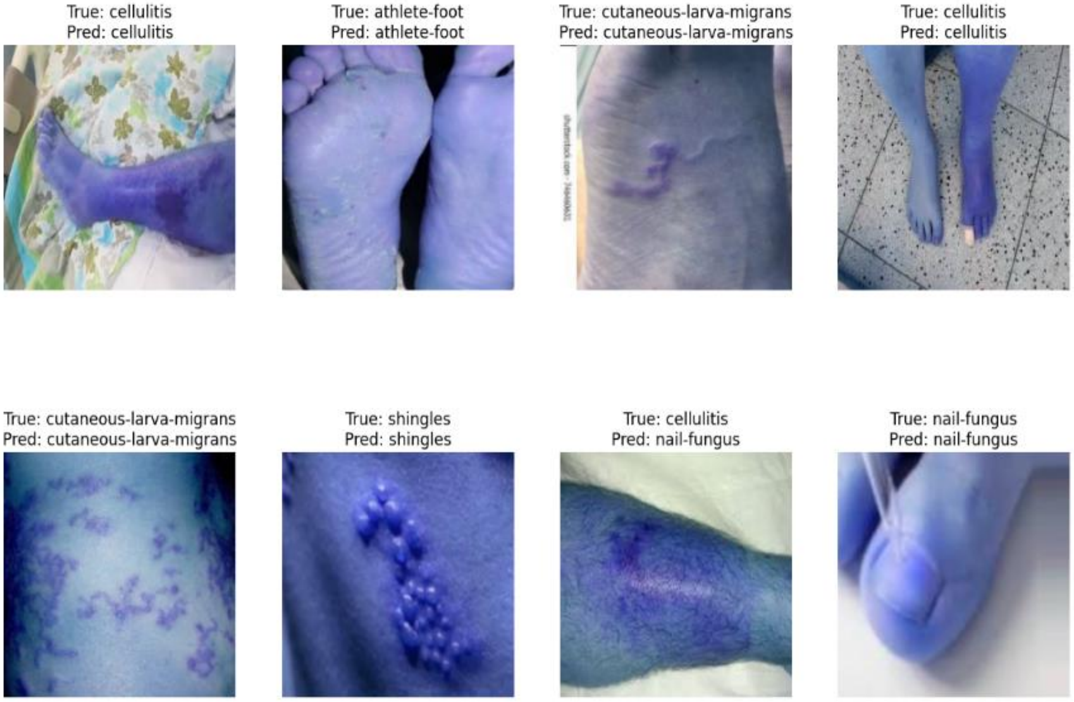


```
Classification Report:
                         precision    recall  f1-score   support

               cellulitis       0.95      0.91      0.93       136
                 impetigo       0.91      0.89      0.90        80
             athlete-foot       0.97      0.96      0.96       124
              nail-fungus       0.89      0.91      0.90       129
                 ringworm       0.93      0.89      0.91        90
cutaneous-larva-migrans       0.92      0.92      0.92       100
               chickenpox       0.96      0.99      0.97       136
                 shingles       0.90      0.94      0.92       130

                 accuracy                           0.93       925
                macro avg       0.93      0.93      0.93       925
             weighted avg       0.93      0.93      0.93       925
```

Figure-8: - Classification Report of CNN Model

The Convolutional Neural Network (CNN) worked well, getting an overall accuracy of 94%.

For cellulitis, the CNN showed a precision of 0. 93 and an F1-score of 0. 91, meaning it performed well and consistently across different categories. CNN was not as accurate with nail fungus, scoring 0. 87, but it did a better job finding true cases, with a score of 0. 93 The even F1-scores for conditions like impetigo and athlete's foot show that the CNN can perform well with different kinds of data.



True: cellulitis
Pred: cellulitis

True: athlete-foot
Pred: athlete-foot

True: cutaneous-larva-migrans
Pred: cutaneous-larva-migrans

True: cellulitis
Pred: cellulitis

True: cutaneous-larva-migrans
Pred: cutaneous-larva-migrans

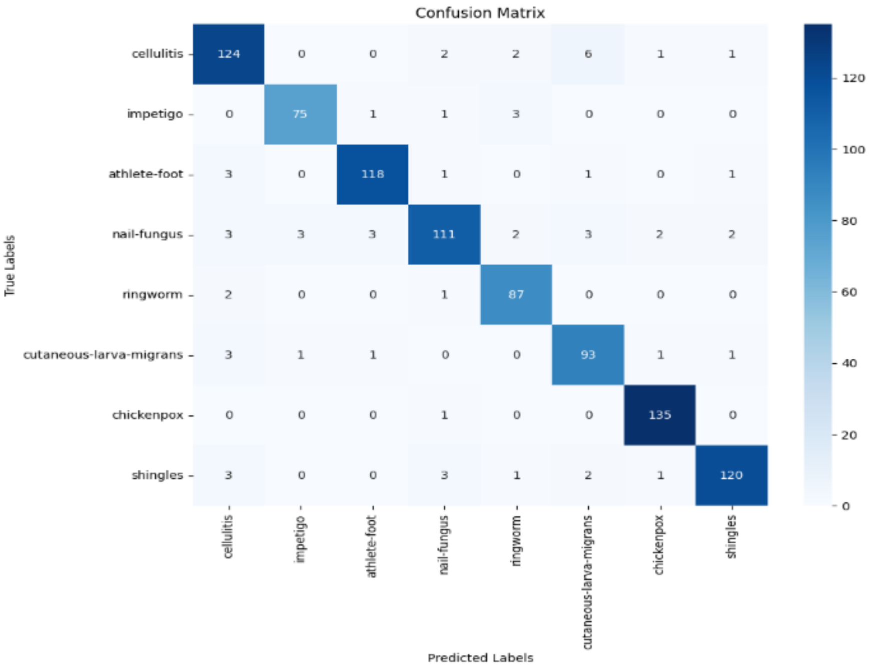
True: shingles
Pred: shingles

True: cellulitis
Pred: nail-fungus

True: nail-fungus
Pred: nail-fungus

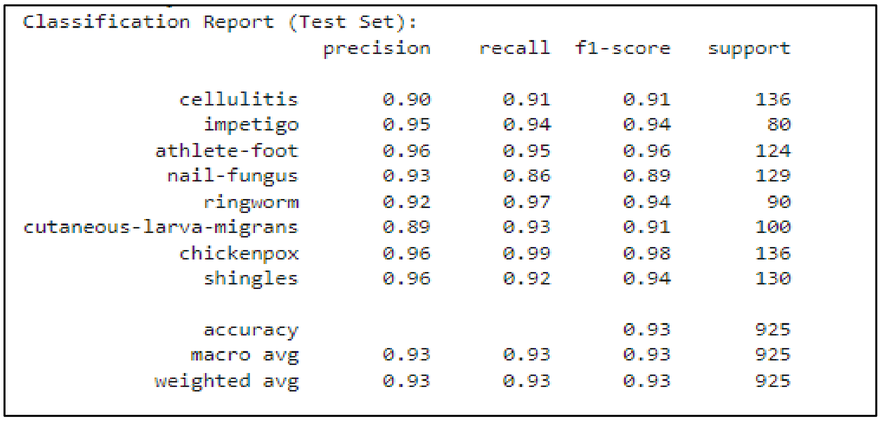
Figure-9: - Prediction by CNN Model

4.2. SVM MODEL: -



	cellulitis	impetigo	athlete-foot	nail-fungus	ringworm	cutaneous-larva-migrans	chickenpox	shingles
cellulitis	124	0	0	2	2	6	1	1
impetigo	0	75	1	1	3	0	0	0
athlete-foot	3	0	118	1	0	1	0	1
nail-fungus	3	3	3	111	2	3	2	2
ringworm	2	0	0	1	87	0	0	0
cutaneous-larva-migrans	3	1	1	0	0	93	1	1
chickenpox	0	0	0	1	0	0	135	0
shingles	3	0	0	3	1	2	1	120

Figure-10: - Confusion Matrix of SVM Model



```
Classification Report (Test Set):
                         precision    recall  f1-score   support

             cellulitis       0.90      0.91      0.91       136
               impetigo       0.95      0.94      0.94        80
           athlete-foot       0.96      0.95      0.96       124
            nail-fungus       0.93      0.86      0.89       129
               ringworm       0.92      0.97      0.94        90
cutaneous-larva-migrans       0.89      0.93      0.91       100
             chickenpox       0.96      0.99      0.98       136
               shingles       0.96      0.92      0.94       130

               accuracy                           0.93       925
              macro avg       0.93      0.93      0.93       925
           weighted avg       0.93      0.93      0.93       925
```

Figure-11: - Classification Report of SVM Model

The Support Vector Machine (SVM) did a good job, achieving an overall accuracy of 93%. SVM did a great job at classifying impetigo, achieving a precision of 0.95 and an F1 score of 0. 94 The model had a bit of trouble with nail fungus. It was less accurate, with a score of 0. 93, and it missed some cases, with a score of 0. 86 Even with these difficulties, SVM stayed strong in many categories, particularly in identifying ringworm, with a high recall rate of 0. 97 This shows that it is good at finding positive cases, even when it has fewer features to work with compared to deep learning models.

4.3. ResNet50 MODEL: -

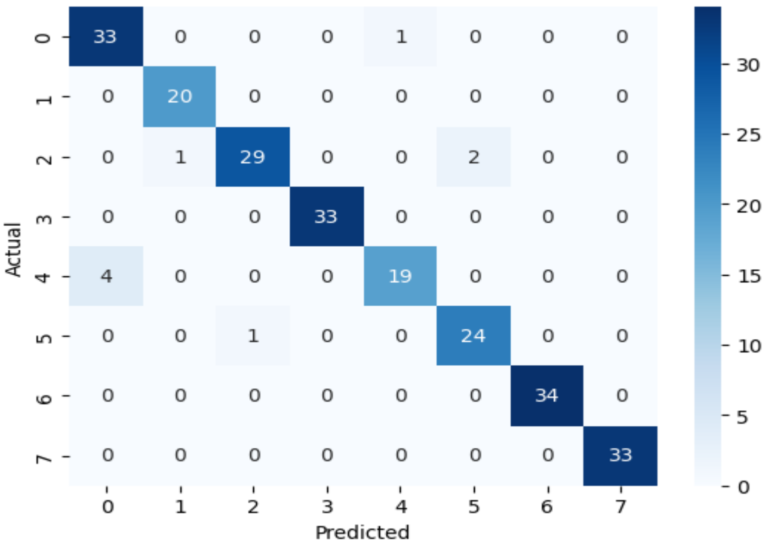


Figure-12: - Confusion Matrix of ResNet50 Model

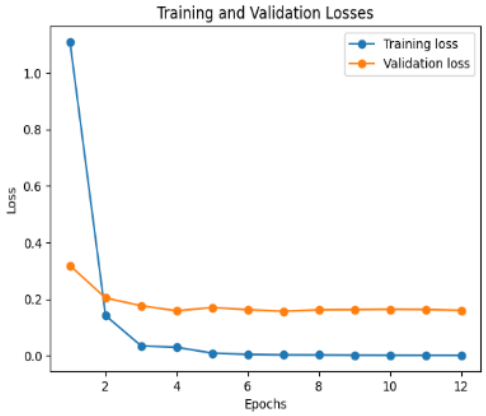

Training and Validation Losses

Figure-13: - ResNet50 Plot [a]

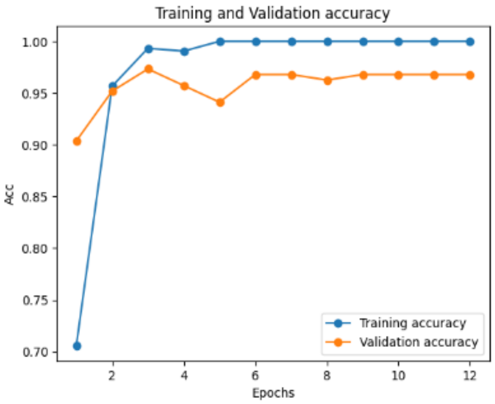

Training and Validation accuracy

Figure-14: - ResNet50 Plot [b]

ResNet50 achieved an overall accuracy of 96%, slightly lower than VGG16 and Mobile-Net but still highly effective. For cellulitis, it achieved a precision of 0.96 and an F1-score of 0.95, demonstrating its ability to capture complex patterns. ResNet50 excelled in athlete’s foot and chickenpox classification, with near-perfect precision and F1 scores. The residual connections in ResNet50 allows for deeper feature extraction, enhancing its performance on more complex images.

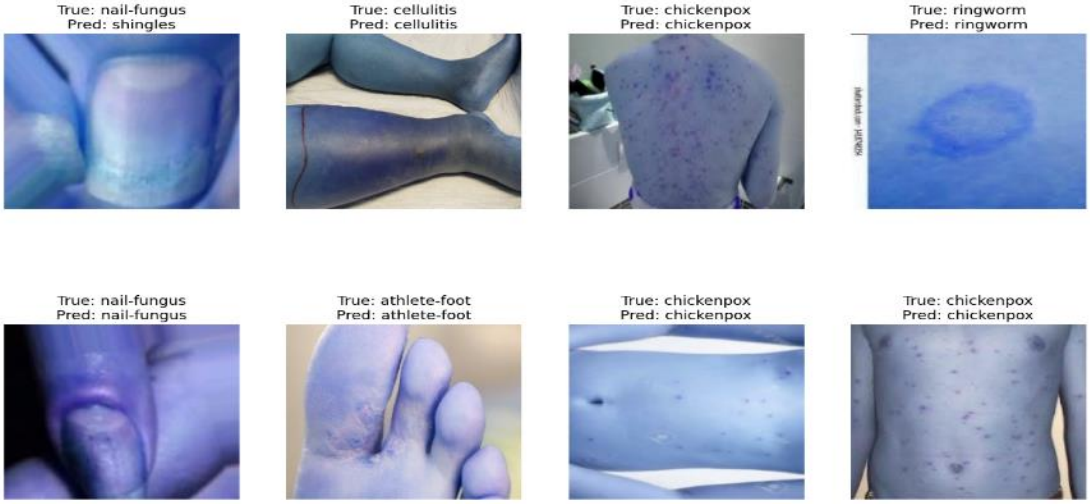
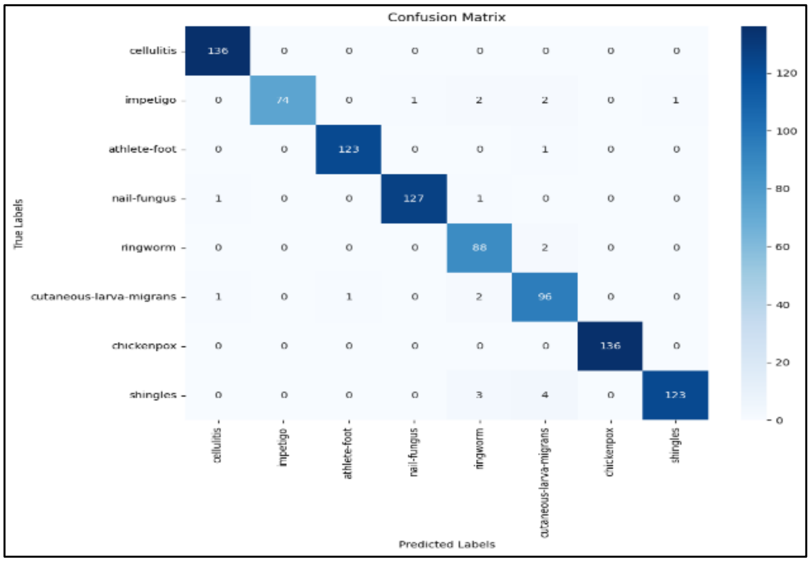


Figure-15: - Prediction by ResNet50 MODEL

4.4. VGG16 MODEL: -


Confusion Matrix

True Labels \ Predicted Labels	cellulitis	impetigo	athlete-foot	nail-fungus	ringworm	cutaneous-larva-migrans	chickenpox	shingles
cellulitis	136	0	0	0	0	0	0	0
impetigo	0	74	0	1	2	2	0	1
athlete-foot	0	0	123	0	0	1	0	0
nail-fungus	1	0	0	127	1	0	0	0
ringworm	0	0	0	0	88	2	0	0
cutaneous-larva-migrans	1	0	1	0	2	96	0	0
chickenpox	0	0	0	0	0	0	136	0
shingles	0	0	0	0	3	4	0	123

Figure-16: - Confusion Matrix of VGG16 Model

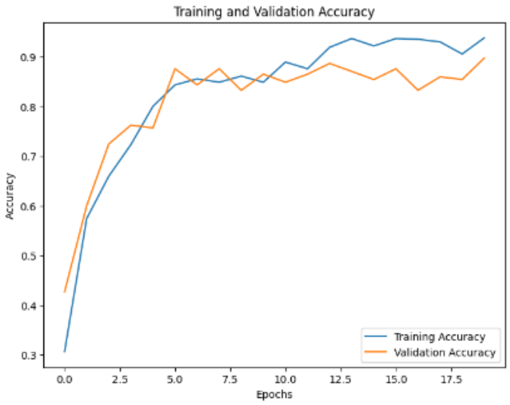


Figure-17: - VGG16 Model Plot [a]

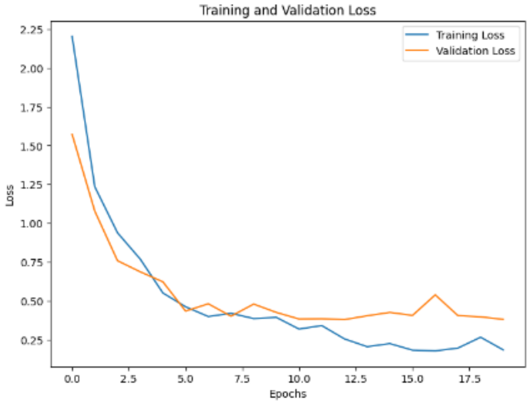
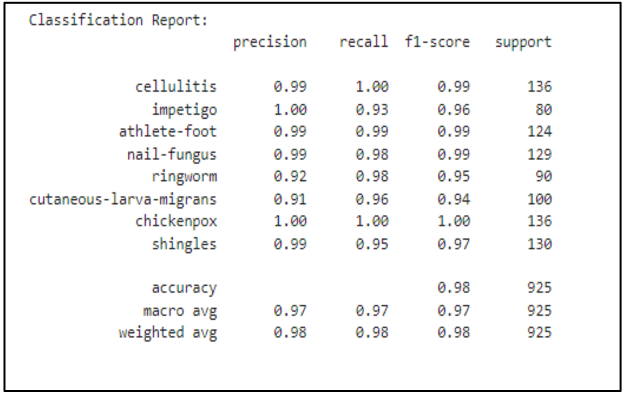


Figure-18: - VGG16 Model Plot [b]



```
Classification Report:
                          precision    recall  f1-score   support

             cellulitis       0.99      1.00      0.99       136
               impetigo       1.00      0.93      0.96        80
            athlete-foot      0.99      0.99      0.99       124
             nail-fungus      0.99      0.98      0.99       129
               ringworm       0.92      0.98      0.95        90
cutaneous-larva-migrans       0.91      0.96      0.94       100
             chickenpox       1.00      1.00      1.00       136
               shingles       0.99      0.95      0.97       130

               accuracy                           0.98       925
              macro avg       0.97      0.97      0.97       925
           weighted avg       0.98      0.98      0.98       925
```

Figure-19: - Classification Report of VGG16 Model

VGG16, a deep learning model, did better than CNN and SVM, achieving an impressive accuracy of 98%. For cellulitis, VGG16 got a perfect recall score of 1. 0 and an F1 score of 0. 99 The model was very consistent across different categories, achieving a perfect score of 1. 0 for chickenpox and nearly perfect scores for other categories like athlete's foot and impetigo. The VGG16 model is very complex, which helped it understand detailed patterns in the skin disease pictures. This made it the most accurate model in this study.

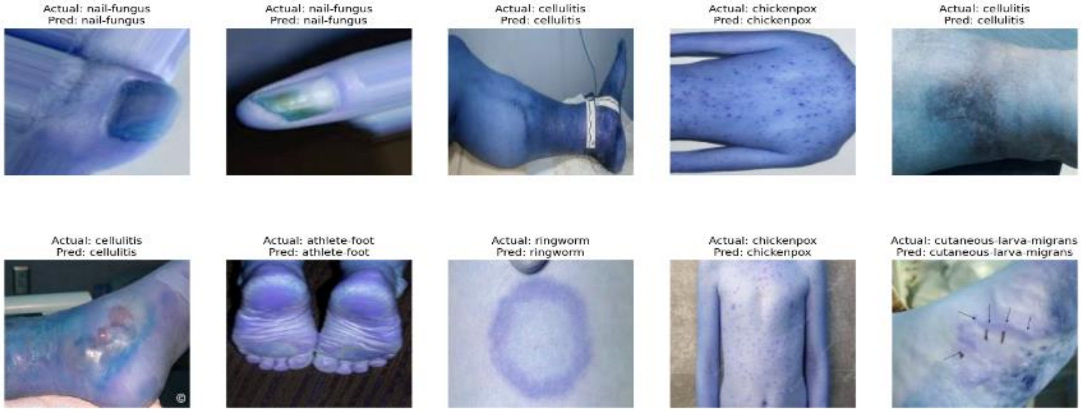


Figure-20: - Prediction by ResNet50 MODEL

4.5. Mobile-Net Model: -

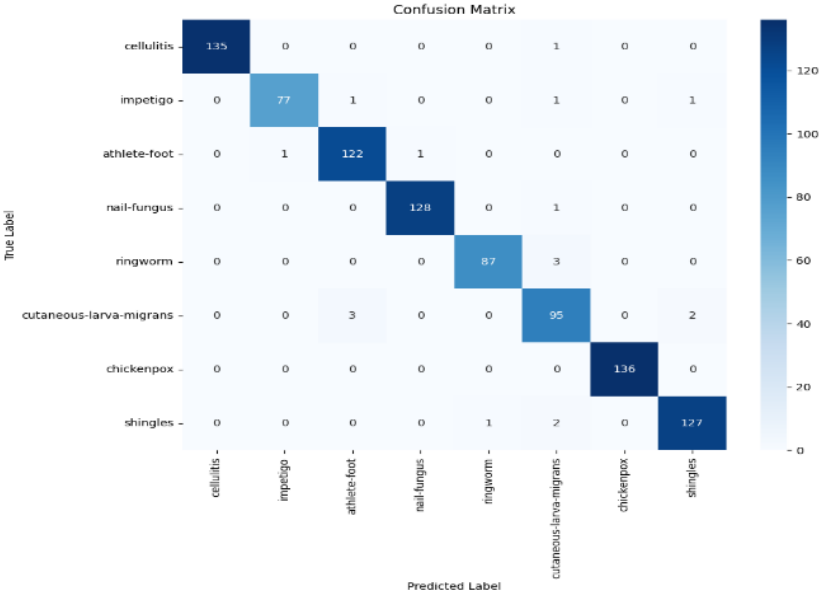


Figure-21: - Confusion Matrix of MobileNet Model

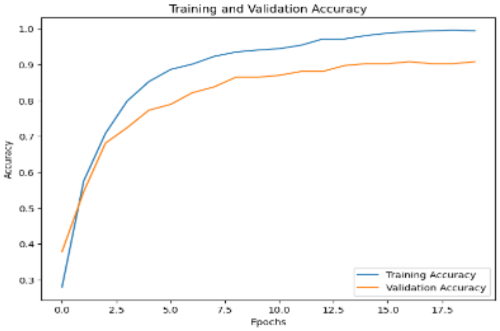


Figure-22: - Mobile-Net Plot [a]

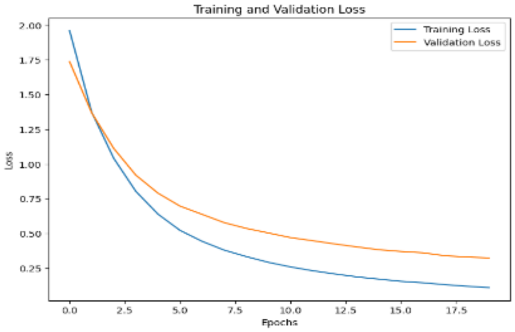
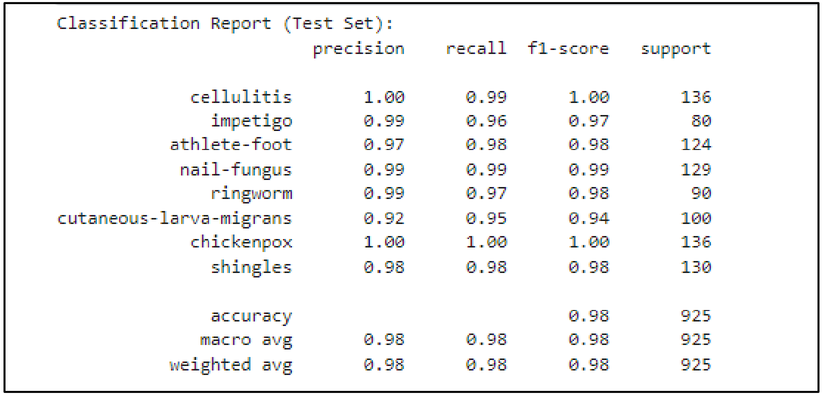


Figure-23: - Mobile-Net Plot [b]



```
Classification Report (Test Set):
                        precision    recall  f1-score   support

             cellulitis       1.00      0.99      1.00       136
               impetigo       0.99      0.96      0.97        80
           athlete-foot       0.97      0.98      0.98       124
            nail-fungus       0.99      0.99      0.99       129
               ringworm       0.99      0.97      0.98        90
cutaneous-larva-migrans       0.92      0.95      0.94       100
             chickenpox       1.00      1.00      1.00       136
               shingles       0.98      0.98      0.98       130

               accuracy                           0.98       925
              macro avg       0.98      0.98      0.98       925
           weighted avg       0.98      0.98      0.98       925
```

Figure-24: - Classification Report of Mobile-Net Model

Mobile-Net, which is built for efficiency, achieved an overall accuracy of 98%, matching VGG16's performance while being a smaller model. Mobile-Net performed perfectly for cellulitis, scoring 1. 0 in both precision and F1-score. It also had almost perfect scores for impetigo and ringworm. Mobile-Net does well in all areas, especially because it has a small and light design. This makes it useful for applications that need to work quickly and efficiently, even when there are limited resources, without losing accuracy.

Overall Model Performance

Table-4.1: - Metrics of all Models

Class	Metric	CNN	SVM	VGG16	MobileNet	ResNet50
Cellulitis	Precision	0.93	0.9	0.99	1	0.96
	Recall	0.9	0.91	1	0.99	0.94
	F1-score	0.91	0.91	0.99	1	0.95
Impetigo	Precision	0.92	0.95	1	0.99	0.97
	Recall	0.91	0.94	0.93	0.96	0.95
	F1-score	0.92	0.94	0.96	0.97	0.96
Athlete-foot	Precision	0.97	0.96	0.99	0.97	0.98
	Recall	0.95	0.95	0.99	0.98	0.97
	F1-score	0.96	0.96	0.99	0.98	0.98
Nail-fungus	Precision	0.87	0.93	0.99	0.99	0.94
	Recall	0.93	0.86	0.98	0.99	0.95
	F1-score	0.9	0.89	0.99	0.99	0.94
Ringworm	Precision	0.94	0.92	0.92	0.99	0.95
	Recall	0.9	0.97	0.98	0.97	0.96
	F1-score	0.92	0.94	0.95	0.98	0.96
Cutaneous-larva-migrans	Precision	0.94	0.89	0.91	0.92	0.93
	Recall	0.95	0.93	0.96	0.95	0.94
	F1-score	0.95	0.91	0.94	0.94	0.93
Chickenpox	Precision	0.97	0.96	1.00	1.00	0.99
	Recall	0.99	0.99	1.00	1.00	0.98
	F1-score	0.98	0.98	1.00	1.00	0.99
Shingles	Precision	0.94	0.96	0.99	0.98	0.97
	Recall	0.93	0.92	0.95	0.98	0.96
	F1-score	0.93	0.94	0.97	0.98	0.96
Overall Accuracy **Macro Average**	Accuracy	0.94	0.93	0.98	0.98	0.96
	Precision	0.94	0.93	0.97	0.98	0.96
	Recall	0.93	0.93	0.97	0.98	0.96
	F1-score	0.93	0.93	0.97	0.98	0.96
Weighted Average	Precision	0.94	0.93	0.98	0.98	0.96
	Recall	0.94	0.93	0.98	0.98	0.96
	F1-score	0.94	0.93	0.98	0.98	0.96

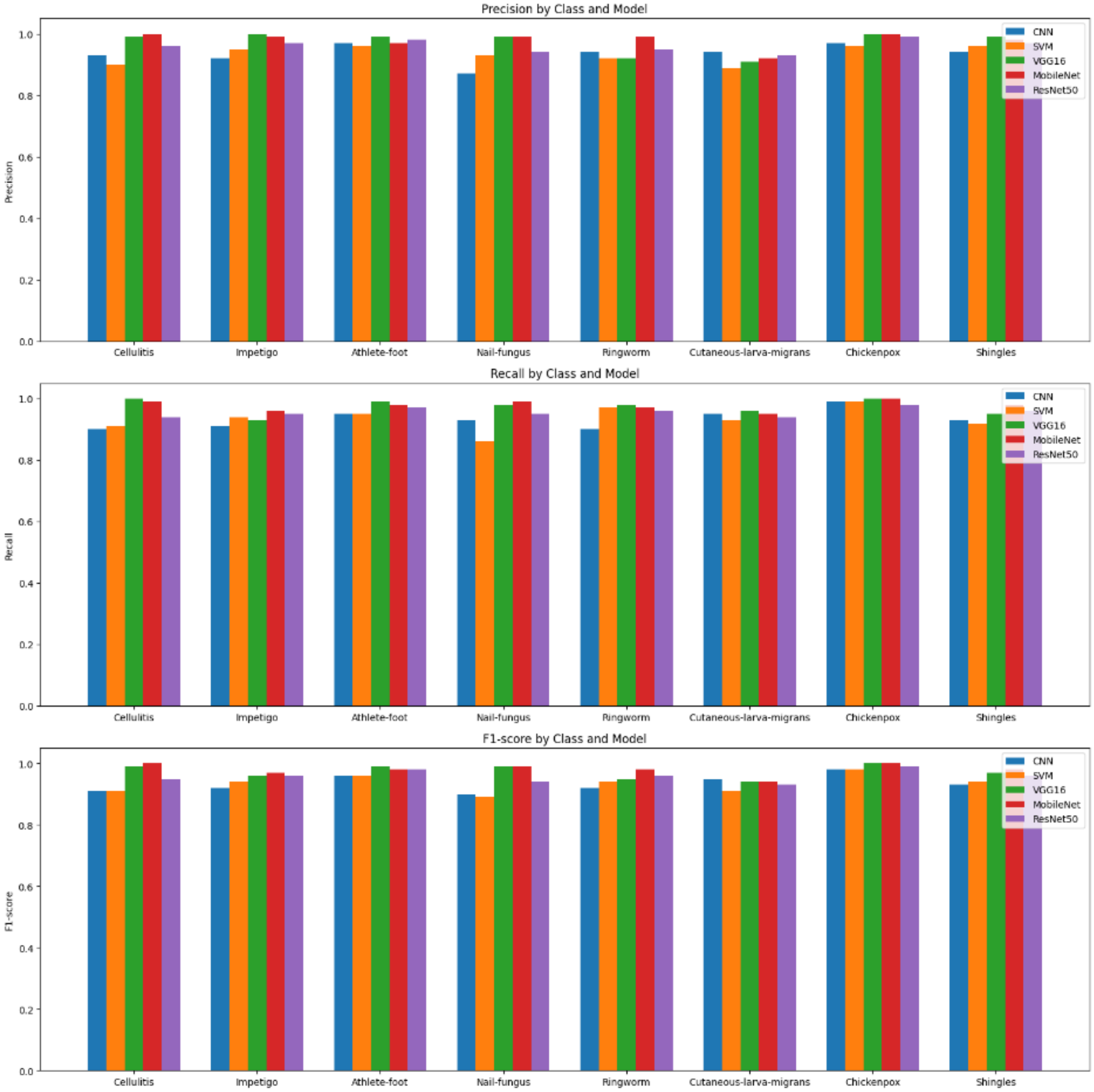


Figure-25: - Visualization by Metrics of all Models

The performance of the models—CNN, SVM, VGG16, Mobile-Net, and ResNet50—was measured using several metrics. These included precision, recall, and F1-score for each type of skin disease, as well as the overall accuracy. The results highlight what each model does well and where it struggles in identifying skin diseases like cellulitis, impetigo, athlete's foot, nail fungus, ringworm, larva migrans, chickenpox, and shingles. When looking at these models, VGG16 and Mobile-Net had the best accuracy, scoring 98%. VGG16 has a deeper design and showed great results for all types of skin diseases, making it the top choice for this classification task. Mobile-Net's similar accuracy with a more effective design shows that it's a good choice for tasks that need quick and efficient processing while still keeping accuracy high. ResNet50 is a little less accurate at 96%, but it did a great job, especially because of its complicated design that uses residual networks. CNN and SVM, while not as accurate as deep learning models, still performed well with overall accuracies of 94% and 93%. This shows that traditional machine learning models, like SVM, can do a good job with medical image classification. However, they might have a harder time picking up small details compared to deeper neural networks. In short, VGG16 and Mobile-Net are the best choices for classifying skin diseases because they are very accurate and perform well in different tests. ResNet50 is also a close runner-up. CNN and SVM did a good job, but deeper models did even better, especially when working with more complicated and detailed patterns in the data.

5. CONCLUSION: -

In this study, we tested five different models—CNN, SVM, ResNet50, VGG16, and Mobile-Net to classify various skin diseases. After careful testing with 80% of the data for training and 20% for checking, the models showed different levels of success in identifying skin diseases like cellulitis, impetigo, athlete's foot, nail fungus, ringworm, cutaneous larva migrans, chickenpox, and shingles. The results show that VGG16 and Mobile-Net are the best models for this task, both reaching a high accuracy of 98%. VGG16 is particularly good because it has a deeper structure and can pick out detailed features better. Mobile-Net works well even though it is lightweight, which makes it a good choice for real-time use in places with few computing resources. ResNet50, using its special connections, did a great job, reaching 96% accuracy and handling complicated image patterns very well. CNN and SVM didn't perform as well as the more complex models, but they still achieved good results with 94% and 93% accuracy, respectively. But using simpler designs made it hard for them to find more complex patterns in the data. The results show that deep learning models, especially VGG16 and Mobile-Net, are beneficial for classifying skin diseases. These models can be used in medical settings to improve how accurately and quickly doctors can diagnose patients and to make it easier for people to get care, especially in places with limited resources. Future research can expand on this study by looking into mixed models and improving their performance for real-life medical use.

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