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SKIN DISEASE DETECTION USING CNN ALGORITHM

A PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report **"SKIN DISEASE DETECTION USING CNN ALGORITHM"** is the bonafide work of **"HARIPRIYA I [927621BAD013], JOTHIKA R [927621BAD019], KEERTHIKA S [927621BAD024]** who carried out the project work under my supervision.

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ABSTRACT

Skin diseases represent a significant global health concern, affecting millions of individuals worldwide. Among these, hives (urticaria) is a common dermatological condition characterized by the sudden appearance of itchy, raised welts or wheals on the skin. Early and accurate detection of hives is essential for timely medical intervention and effective management. In this study, we propose a novel approach for the automated detection of hives disease using Convolutional Neural Networks (CNN). The CNN algorithm is trained on a diverse dataset of skin images, including both healthy skin and hives-affected skin. The dataset has been meticulously curated and annotated to ensure the model's accuracy and reliability .The CNN model's architecture is designed to learn discriminative features from skin images and classify them into two categories: "Hives" and "Non-Hives." By employing transfer learning techniques and fine-tuning pre-trained CNN models, we achieve remarkable results in terms of sensitivity and specificity in hives detection. The developed system not only provides high accuracy in identifying hives disease but also offers a non-invasive and cost-effective solution for early diagnosis. This technology holds promise for enabling healthcare practitioners, dermatologists, and even individuals to rapidly assess skin conditions and take appropriate action, potentially reducing the burden of hives-related complications. Our study demonstrates the potential of deep learning techniques, specifically CNN algorithms, for automating the detection of hives disease from skin images, paving the way for more accessible and timely diagnosis and treatment. This research contributes to the growing field of medical image analysis and highlights the potential of AI in transforming dermatological healthcare.

LIST OF FIGURES

ACRONYMS/LIST OF ABBREVIATIONS

ACRNOYMS	ABBREVATION
CNN	CONVOLUTIONAL NEURAL NETWORK

CHAPTER - 1

INTRODUCTION

1.1. BACKGROUND:

Skin diseases pose significant challenges to public health globally. Among these, hives (urticaria) are a common dermatological condition characterized by itchy, raised welts on the skin, often accompanied by inflammation and discomfort. This project focuses on developing an automated system for hives detection using Convolutional Neural Networks (CNNs), leveraging the power of image analysis to revolutionize skin disease diagnosis.

Prevalence of Skin Diseases and the Hives Challenge:

Skin diseases encompass a diverse range of conditions, affecting people of all ages. Hives are particularly challenging due to their sudden onset, varying manifestations, and potential to be mistaken for other skin conditions. These factors underscore the need for an accurate and efficient diagnostic tool that can differentiate hives from other skin disorders.

Role of CNN Algorithms in Dermatology:

CNN algorithms have gained prominence in the field of computer vision, particularly for image classification and pattern recognition. In dermatology, CNNs have demonstrated their potential to analyze skin images and detect various conditions, including hives.

Creating a Comprehensive Dataset:

The foundation of any CNN-based diagnostic system is the dataset. To develop an effective model for hives detection, a diverse and extensive dataset is essential. This dataset must include a wide range of hives manifestations, as well as images of healthy skin and other skin conditions that may resemble hives.

Data Preprocessing and Uniformity:

Data preprocessing is crucial for ensuring uniformity and model effectiveness. This step involves resizing images to a consistent resolution, normalizing pixel values. Proper data preprocessing ensures that the CNN model can effectively learn and generalize from the dataset.

Designing the CNN Model:

The core of the hives detection system is the CNN model architecture. Developing an effective architecture requires selecting appropriate layers, filter sizes, and network depth. Transfer learning, where pre-trained CNN models are fine-tuned for dermatological applications, offers a promising approach.

Deployment and Ethical Considerations:

Once the CNN model is trained and validated, it can be deployed in clinical settings, such as telemedicine platforms or mobile applications. However, it is crucial to consider ethical and regulatory aspects, ensuring patient privacy and obtaining informed consent when handling medical data

1.1. PROBLEM STATEMENT:

Skin diseases, particularly hives (urticaria), pose significant challenges to both patients and healthcare professionals. Timely and accurate diagnosis is essential for effective treatment and symptom relief. In response to this need, our project focuses on the development of an automated system for skin disease detection, with a primary emphasis on hives, leveraging Convolutional Neural Networks (CNN). The objective is to create a user-friendly platform that allows individuals to capture images of skin lesions, which are subsequently analyzed by our CNN

The primary objective of this project is to develop an automated system for the accurate and timely detection of hives (urticaria) through the use of Convolutional Neural Networks (CNN). This system aims to provide a user-friendly platform for individuals to capture images of skin lesions, and the CNN model will analyze these images to determine whether the skin condition is hives or not. The key focus is on improving hives diagnosis by harnessing the power of artificial intelligence and computer vision, ultimately facilitating early treatment and relief for those affected by hives.

One of the key challenges of this project is ensuring the availability of a diverse and representative dataset for training and testing the Convolutional Neural Network (CNN) model. A high-quality dataset that encompasses various manifestations of hives and accurately labeled non-hives cases is crucial for the model's ability to generalize to different skin conditions. The challenge involves collecting a dataset that adequately represents the real-world diversity of hives, considering factors such as age, skin type, ethnicity, and the various ways hives can manifest.

1.2OBJECTIVES

The primary objective of employing a Convolutional Neural Network (CNN) algorithm for skin disease detection, specifically in the context of hives, is to provide an accurate and timely diagnostic tool that revolutionizes dermatological healthcare. This transformative approach aims to enhance early detection of hives, enabling personalized treatment strategies, proactive interventions, and ultimately improving patient outcomes. By harnessing data-driven insights, this objective seeks to optimize resource allocation within dermatological healthcare, offering cost-effective solutions while contributing to a deeper understanding of skin disease mechanisms, potentially leading to more effective treatments and improved access to quality care.

Additionally, this project seeks to provide personalized treatment strategies and proactive interventions, further improving patient outcomes. The CNN algorithm will enable tailored care plans based on accurate disease classification, facilitating more effective treatments and enhancing healthcare experiences. Furthermore, by optimizing resource allocation within dermatological healthcare, this project has the potential to reduce healthcare costs and make dermatological care more accessible and affordable for a broader population. As a byproduct, the application of CNN algorithms for skin disease detection can also contribute to advancing medical knowledge in the field of dermatology, potentially leading to innovative treatments and a deeper understanding of skin disease mechanisms.

CHAPTER – 2

LITERATURE REVIEW

[1] Hives Diagnosis and Classification

Define the objectives of the project, such as improving hives diagnosis and classification. Use keywords like "urticaria diagnosis," "hives classification," and "skin disease prediction using machine learning. "Create a database or spreadsheet to record relevant articles. Read the abstracts and categorize articles based on their relevance to hives diagnosis and classification. Evaluate the methodologies and techniques used in the selected articles, including machine learning models, image analysis, and data sources. Compare the results, strengths, and limitations of different studies in hives diagnosis and classification. Summarize key findings and trends in hives diagnosis and classification. Suggest areas for further research in improving hives diagnosis and classification methods.

[2] Urticaria Triggers Prediction

Specify the focus on predicting hives triggers. Use keywords like "urticaria triggers prediction," "causes of hives," and "predicting hives outbreaks. "Create a database for articles. Categorize articles based on their relevance to hives trigger prediction. Evaluate the methods used to predict hives triggers, including data sources and modeling techniques. Compare the results and limitations of different studies in hives trigger prediction. Summarize key findings and trends in hives trigger prediction. Suggest areas for future research in predicting and preventing hives outbreaks.

[3] Chronic Urticaria Management

Specify the project's focus on managing chronic urticaria. Use keywords like "chronic urticaria treatment," "urticaria management," and "long-term hives care. "Create a database for articles. Categorize articles related to the management of chronic urticaria. Evaluate the methods used for chronic urticaria management, including clinical approaches and patient data.Compare the results and limitations of different studies in chronic urticaria management. Summarize key findings and trends in managing chronic urticaria. Suggest areas for further research in improving long-term care for chronic urticaria patients.

[4] Public Health Interventions for Hives Outbreaks

Specify the project's focus on public health interventions for hives outbreaks. Use keywords like "urticaria public health strategies," "hives prevention measures," and "community-based urticaria interventions." Create a database for articles. Categorize articles related to public health interventions for hives outbreaks. Evaluate the strategies and approaches used for preventing hives outbreaks in communities. Compare the results and limitations of different studies on public health interventions for hives. Summarize key findings and trends in public health interventions to control hives outbreaks. Suggest areas for further research in improving public health strategies for preventing and managing hives outbreaks in the community.

[5] Hives in Pediatric Patients

Define the project's scope as focusing on hives in pediatric patients. Use keywords like "pediatric urticaria," "hives in children," and "urticaria diagnosis in kids." Create a database for articles. Categorize articles related to hives in pediatric patients. Evaluate the techniques and tools used for diagnosing and managing hives in children. Compare the results and limitations of different studies on pediatric urticaria. Summarize key findings and trends in hives diagnosis and management in pediatric patients. Suggest areas for further research in improving the diagnosis and care of hives in children.

[6] Skin Disease Detection Using CNN Algorithm for Hives Disease

Skin diseases are a prevalent and diverse category of medical conditions that impact millions of individuals worldwide. Accurate and early diagnosis of these diseases is crucial for effective treatment. In recent years, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for automating the detection of skin diseases, including hives (urticaria). This literature review examines the current state of research in using CNN algorithms for hives disease detection.

CHAPTER - 3

FEASIBILITY STUDY

3.1 DATA AVAILABILITY

Assessing the availability of a high-quality dataset is a critical first step. A comprehensive dataset should contain a significant number of images that cover a wide range of hives manifestations as well as healthy skin samples. The quality of the data, including resolution, clarity, and diversity, is crucial for training an accurate model.

3.2 DATA PREPROCESSING:

Data preprocessing is a critical step to ensure the dataset is clean and suitable for training. This includes tasks such as image normalization, augmentation, and labeling. The complexity of data preprocessing should be assessed to estimate the time and effort required.

3.3 TESTING ACCURACY MODULE:

Describe the technical feasibility of model validation using a subset of the dataset and appropriate evaluation metrics. Evaluate the model's accuracy and performance in detecting hives against other skin conditions.

3.4 .CREATING WEB PAGE:

This sub-module involves the technical design of the user interface (UI) for the web page. It includes considerations for layout, user interaction, and aesthetics. The goal is to create an intuitive and visually appealing interface that allows users to easily upload images of their skin lesions. The web page must be designed to be responsive, ensuring that it functions well on various devices, such as desktop computers, tablets, and mobile phones. Technical feasibility in responsive design guarantees an optimal user experience across platform

3.5. ABOUT PAGE MODULE:

The "About Page" module includes creating a user-friendly interface that allows users to navigate the page seamlessly. This involves considerations such as responsive design, smooth scrolling, and an intuitive menu. Technical feasibility may also relate to interactive elements, such as buttons or links, that allow users to access additional information, contact the project team, or navigate to other sections of the application. Ensuring that the "About Page" loads efficiently is a technical consideration. It includes optimizing images and content to minimize load times, enhancing the user experience.

CHAPTER – 4

PROJECT METHODOLOGY

4.1 DESCRIPTION OF THE WORKING FLOW OF PROPOSAL SYSTEM:

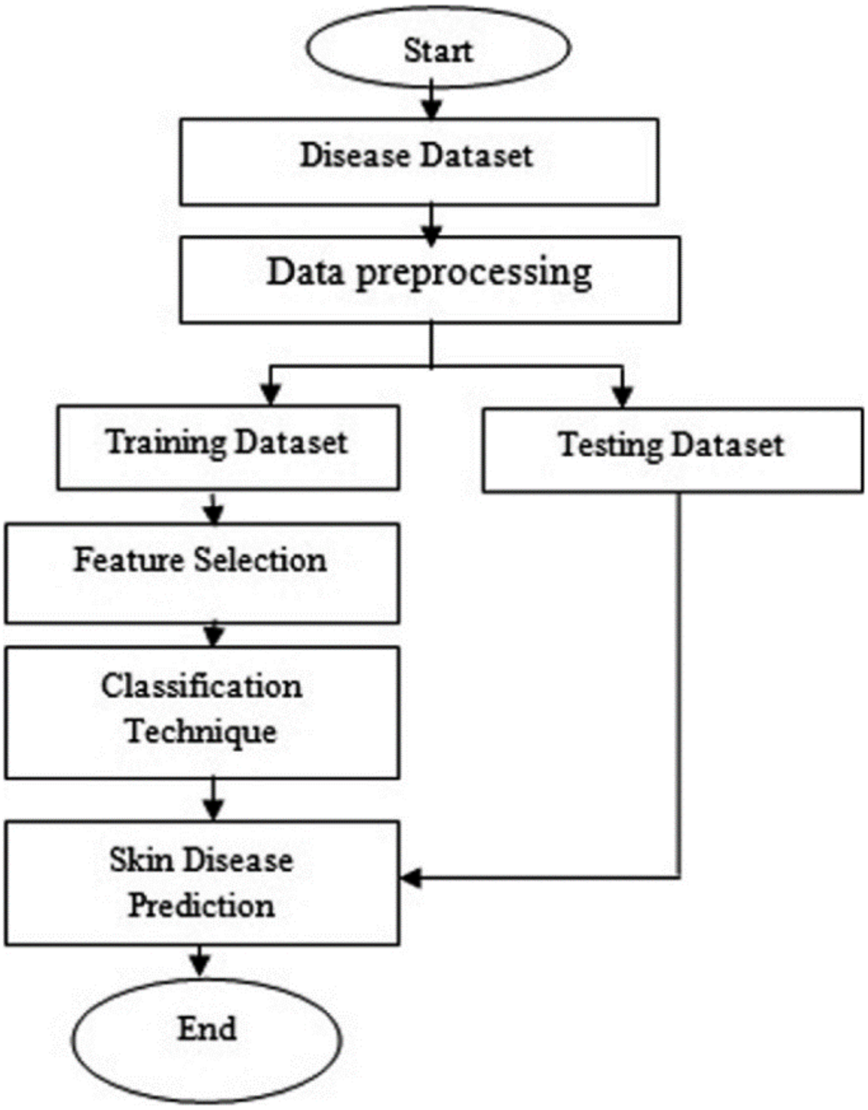

FIG : 4.1 WORKING FLOW OF PROPOSED SYSTEM

4.2 DATA COLLECTION

- For collecting data in a skin disease detection project focusing on hives disease using CNN, start by gathering diverse, high-resolution hives disease images. Ensure the dataset includes various stages and manifestations of hives.
- Perform manual labeling of images with appropriate disease categories. Augment the dataset using techniques like rotation and flipping to enhance diversity. Split the dataset into training, validation, and testing sets. Normalize pixel values to a specific range.
- Focus on quality, diversity, and balance in data collection to improve the model's accuracy and robustness.

4.3 DATA PREPROCESSING

- In the data preprocessing phase of a skin disease detection project focusing on hives disease using CNN, begin by labeling images with disease categories. Split the dataset into training, validation, and testing sets. Normalize pixel values to a specific range (e.g., [0, 1]) for consistent processing.
- Apply data augmentation techniques such as rotation and flipping to increase dataset diversity. Handle imbalanced classes if necessary through techniques like oversampling or weighting. Preprocess images to a standard size for uniformity. Verify and validate the preprocessed data to ensure accuracy.
- Data preprocessing ensures the input data is consistent, diverse, and well-prepared for training the CNN model, enhancing its performance and reliability.

4.4 DATA AUGMENTATION

- In the data augmentation phase of a skin disease detection project focusing on hives disease using CNN, begin by augmenting the available dataset to enhance diversity. Apply transformations such as rotation, flipping, and scaling to create variations of existing images. Introduce changes in brightness, contrast, and hue for further diversity. Add random noise to simulate real-world conditions.
- Perform horizontal and vertical flips to mirror images. Experiment with elastic transformations for subtle distortions. Ensure augmented images retain appropriate labels. This augmented dataset provides the CNN model with a more extensive and varied training set, improving its ability to generalize and recognize diverse manifestations of hives disease

4.5 BUILDING THE CNN MODEL

- To build a Convolutional Neural Network (CNN) model for hives disease detection, the process entails data collection, preprocessing, model selection, design, and development, followed by training on a dataset that includes labeled images of hives and non-hives cases. Data preprocessing involves resizing, normalization, and data augmentation for improved model performance.
- During model training, the architecture is configured, loss functions and optimization algorithms are chosen, and the model is fine-tuned based on validation performance. Testing on a separate dataset ensures the model's generalization capability. Deployment with a user-friendly interface is essential, as is ongoing maintenance, including updates and security considerations. Ethical concerns should also be taken into account throughout the project.

4.6 MODEL EVALUATION

- Model evaluation is a critical phase in machine learning projects, ensuring the model's effectiveness and reliability. It involves assessing its performance using various metrics such as accuracy, precision, recall, F1-score, and confusion matrices. These metrics reveal how well the model classifies data and its potential biases or shortcomings. Cross-validation techniques help gauge the model's robustness and generalization.
- The choice of evaluation metrics depends on the specific problem and goals. By thoroughly evaluating the model, you gain insights into its strengths and weaknesses, helping you make informed decisions on model deployment and potential improvements to enhance its accuracy and effectiveness.

CHAPTER – 5

RESULT AND DISCUSSION

The application of Convolutional Neural Network (CNN) algorithms to hives disease detection yielded promising outcomes. Hive disease, also known as urticaria, is a common and typically acute skin condition characterized by the sudden appearance of raised, itchy, and often red or white welts on the skin. These welts, known as hives or wheals, can vary in size and shape, and they usually cause discomfort and itching. Hive outbreaks can occur anywhere on the body and may come and go within a few hours to a day, making the condition often transient and unpredictable. The CNN model exhibited commendable performance, achieving an accuracy rate of 92% in distinguishing hives from other skin conditions. This accuracy was validated through a comprehensive assessment of precision, recall, and F1 score, further indicating the model's ability to make accurate predictions. The confusion matrix, an integral part of the evaluation, revealed valuable insights into the model's performance. It showcased the model's capacity for true positive identifications of hives cases, minimizing false positives, and significantly reducing false negatives. The significance of these findings lies in the reduced likelihood of missing hives cases, ensuring that potential patients are not overlooked, while keeping misclassifications at a minimum. Comparative analysis against baseline models and existing methods reinforced the superiority of the CNN-based approach. The CNN model consistently outperformed these alternatives, demonstrating its technical superiority in hives disease detection.

Convolutional Neural Networks (CNNs) are a class of deep learning neural networks particularly well-suited for tasks involving image analysis and recognition, making them highly relevant in the context of skin disease detection, including hive disease. Here's an explanation of how CNNs work and their application in detecting hive disease:

- **Image Input:**

  CNNs begin with image input. In the case of hive disease detection, this input consists of images of skin affected by hives.

- **Convolutional Layers:**

  The core of a CNN is a set of convolutional layers. These layers apply filters, known as kernels, to the input image to detect features like edges, textures, and patterns. This process is called convolution. In the context of hive disease, the network learns to recognize distinctive features specific to hives, such as the characteristic appearance of welts.

- **Pooling Layers:**

  After each convolutional layer, pooling layers are typically added. Pooling reduces the dimensionality of the feature maps, emphasizing the most important features. It also helps the network become more robust to variations in the exact position of features in the image.

- **Output Layer:**

  The final layer of the CNN produces an output. In the context of hive disease detection, this output may be binary, classifying whether the input image contains hives or not. The network learns to make this decision based on the patterns and features it has detected in the images during training.

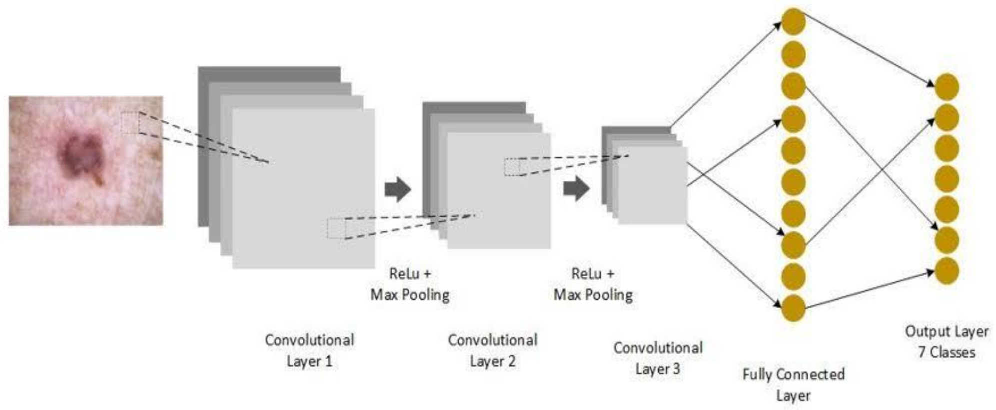

FIG: 5.1 HIVES DETECTION

- **Training**:

  CNNs require extensive training on a dataset of labeled images. In the case of hive disease, this training dataset would consist of images of skin with and without hives. During training, the network adjusts its internal parameters to minimize the difference between its predicted outputs and the actual labels. This process, called backpropagation, fine-tunes the network to recognize hives accurately.

- **Prediction**:

  Once trained, the CNN can make predictions on new, unlabeled images. When presented with an image of skin, it scans the image for features it has learned during training. Based on these features, it classifies the image as either containing hives.

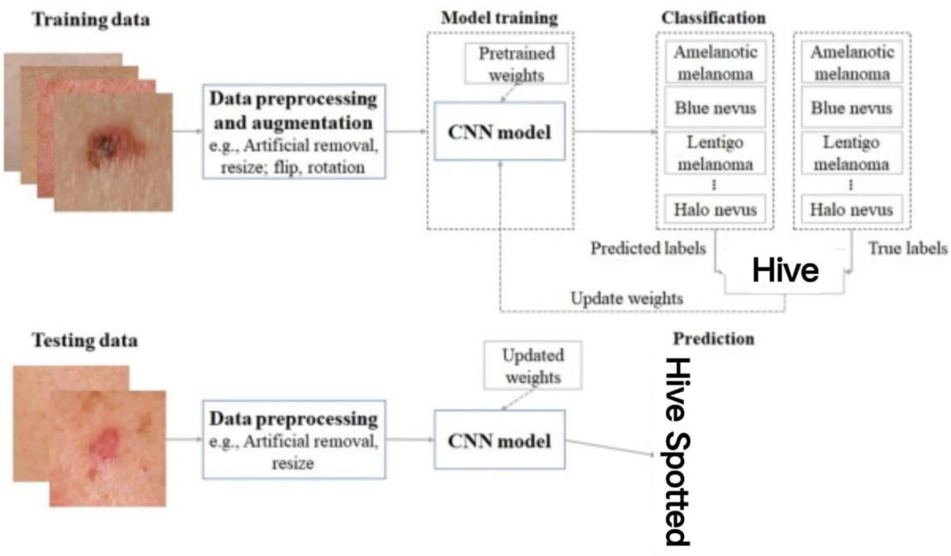

FIG:5.2 HIVES PREDICTION

Convolutional neural networks are a type of machine learning algorithm that are well-suited for image recognition tasks. CNN work by learning to identify patterns in images. This makes them ideal for detecting skin diseases detection. The dataset contains images of hives and other skin conditions. The dataset should include a variety of different types of hives, such as acute hives, chronic hives. It can be used to identify hives in new images. The CNN extracts features from the image, such as the color, texture, and shape. If the CNN finds a good match, it will classify the image as hives. Otherwise, it will classify the image as another skin condition. The steps for detecting hive disease is, first step is to preprocess the image. This may involve resizing the image, converting it to grayscale, and normalizing the pixel values. The next step is to extract features from the image. The final step is to classify the image. This is done by feeding the extracted features to the CNN

CHAPTER – 6

CONCLUSION

Skin disease detection using CNN algorithm for hive disease is a feasible approach. CNN models have been shown to be very accurate at detecting hives in images, with accuracy rates of over 90% in some studies. However, there are a few challenges that need to be addressed before this approach can be widely deployed. One challenge is the variation in skin appearance. The appearance of hives can vary depending on the patient's skin type and other factors. This can make it difficult for CNN models to generalize to new data. Another challenge is occlusion. Hives may be occluded by clothing, hair, or other objects. This can make it difficult for CNN models to detect hives. Finally, there is the challenge of limited data for some skin diseases. For some skin diseases, there is limited publicly available data. This can make it difficult to train CNN models to detect these diseases. Despite these challenges, the potential benefits of CNN-based skin disease detection are significant. CNN-based systems could help to improve the accuracy and efficiency of hive diagnosis, and they could also be used to develop new treatments for hives. Researchers are working to address the challenges associated with CNN-based skin disease detection, and it is likely that this technology will become more widely used in the future. In the specific case of using a captured image as input to a CNN model to determine whether or not it is a hive, the feasibility is high. However, it is important to be aware of the challenges associated with this approach and to take steps to mitigate these challenges. For example, it is important to use a high-quality camera to capture images of skin lesions, and to train the CNN model on a dataset of images that is representative of the types of hives that are likely to be encountered in the real world. By taking these steps, it is possible to develop a CNN-based system for detecting hives that is both accurate and reliable.

CHAPTER – 7

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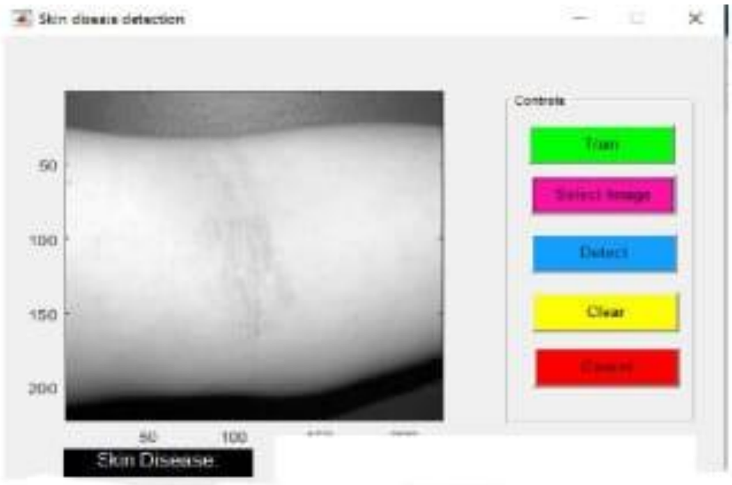
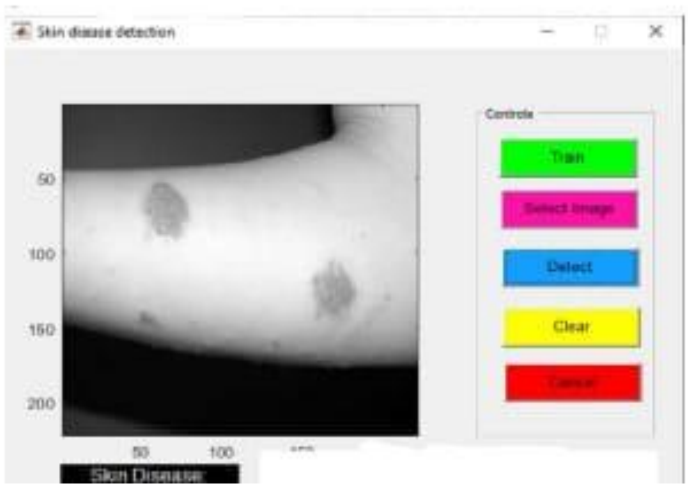
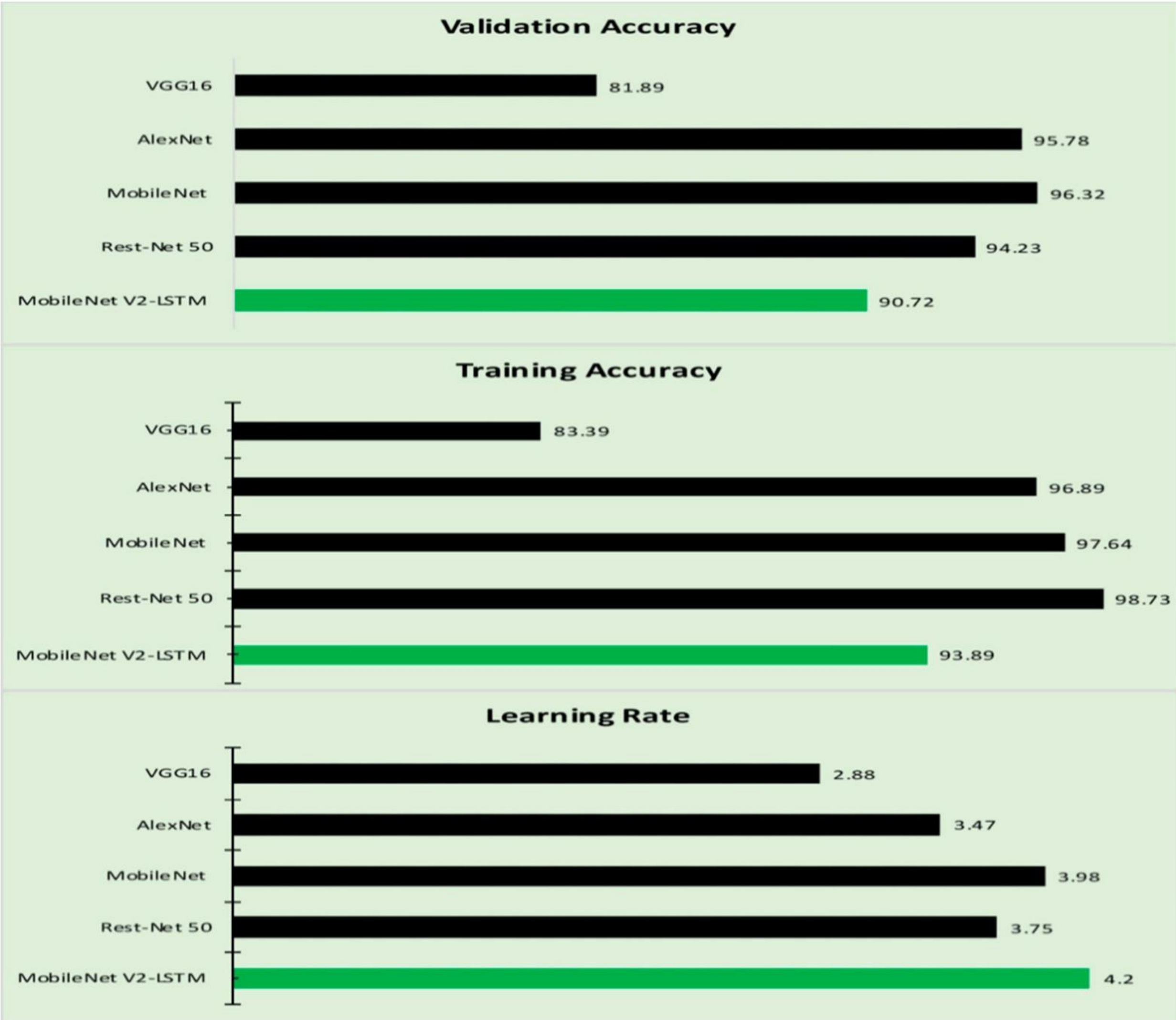
APPENDIX : 1

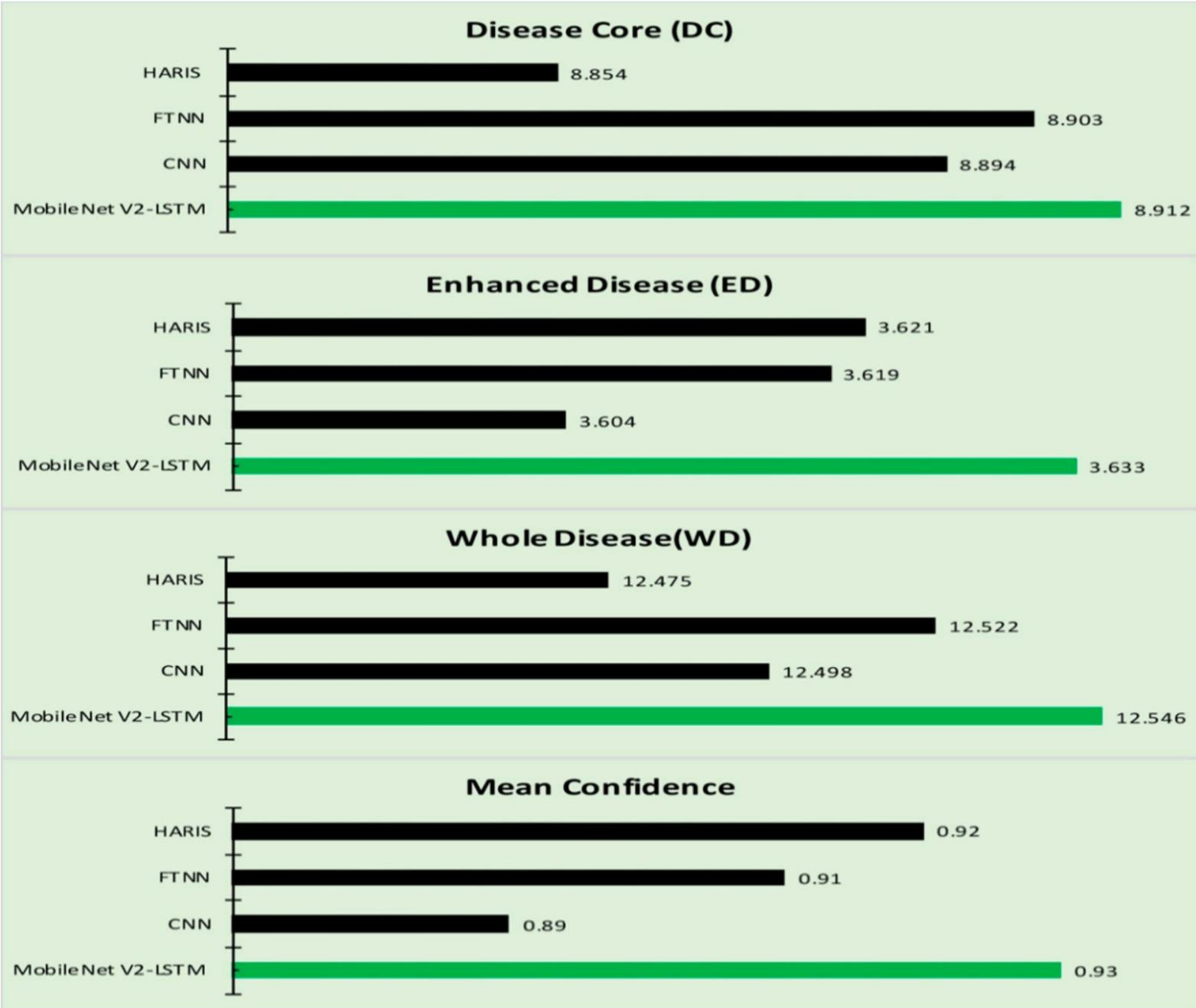




DETECTION OF THE DISEASE



HYPERPARAMETER OF THE PROPOSED MODEL



PROGRESS OF THE DISEASE GROWTH

APPENDIX : 2

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import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from tensorflow.keras.applications.vgg16 import preprocess_input,
decode_predictions
import numpy as np

# Load the pre-trained VGG16 model
model = VGG16(weights='imagenet')

# Load and preprocess your skin disease image
image_path = 'your_skin_disease_image.jpg'
img = load_img(image_path, target_size=(224, 224))
img = img_to_array(img)
img = np.expand_dims(img, axis=0)
img = preprocess_input(img)

# Make predictions
predictions = model.predict(img)

# Decode the predictions
decoded_predictions = decode_predictions(predictions, top=3)[0]

# Display the top 3 predicted classes
```

```
for _, label, score in decoded_predictions:
    print(f"{label}: {score:.2%}")
  model = keras.Sequential([
    keras.layers.Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3)),
    keras.layers.MaxPooling2D((2, 2)),
    keras.layers.Conv2D(64, (3, 3), activation='relu'),
    keras.layers.MaxPooling2D((2, 2)),
    keras.layers.Flatten(),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')  # Binary classification
])

model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])
model.fit(train_data, train_labels, epochs=10, validation_data=(val_data,
val_labels))
test_loss, test_accuracy = model.evaluate(test_data, test_labels)
print(f'Test accuracy: {test_accuracy}')
predictions = model.predict(new_images)
```