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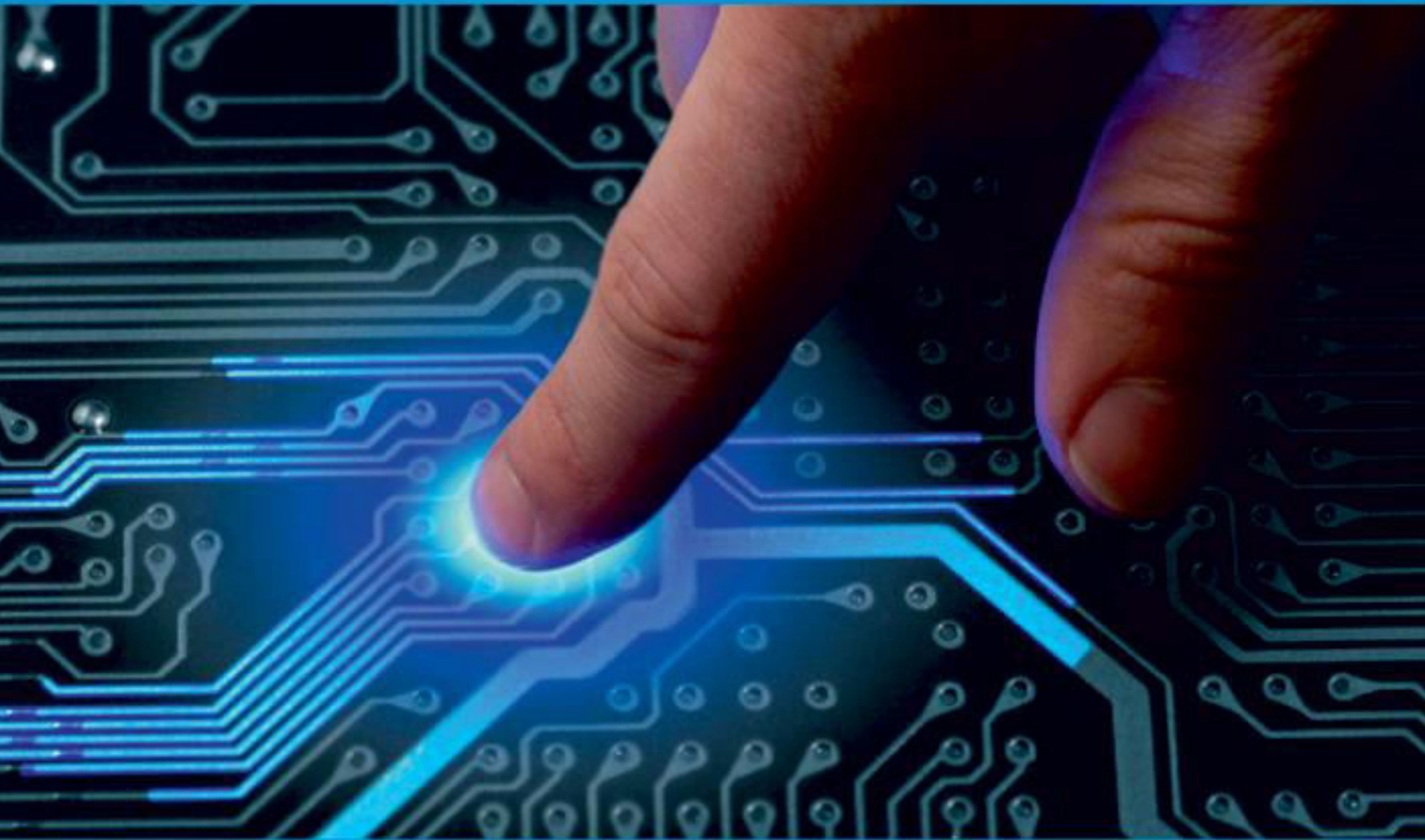

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Skin Disease Detection Using ML

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ABSTRACT: Skin diseases are a prevalent type of infection among individuals of all times. However, the high cost of hiring dermatologists to observe patients has led to a need for a computerized system to assess a patient's risk of skin disease using images of their skin problems. Researchers have employed various pre-processing and classification techniques to determine whether a skin image is affected by a disease or not. Feature extraction plays a crucial role in predictive modelling applications, where it involves capturing the visual content of images for retrieval and indexing. Texture-based features are commonly used in medical image analysis for skin disease recognition. Detecting and observing skin diseases is a significant challenge faced by the medical industry, as the prevalence of skin-related issues is increasing rapidly due to rising pollution and poor dietary habits. Machine learning algorithms can aid in the development of effective systems that can classify different types of skin diseases. To identify skin diseases, it is necessary to first separate skin and non-skin areas. This research paper employs five distinct machine learning algorithms on a skin infection dataset to accurately predict the class of skin disease. Machine learning models, like convolutional neural networks , are commonly used for skin disease detection. These models learn from labelled skin image datasets, associating each image with a specific diagnosis. Through this learning process, the models identify complex patterns and make predictions about the presence of specific skin diseases in new, unseen images.

KEYWORDS: prevalent, dermatologists, retrieval, dietary, diagnosis,patterns.

I. INTRODUCTION

1.1 Overview

Skin disease detection is the process of identifying and diagnosing various skin conditions through visual examination and analysis. Skin diseases encompass a wide range of conditions that affect the skin, such as acne, psoriasis, eczema, dermatitis, melanoma, and many others. Detecting and diagnosing these conditions accurately and in a timely manner is crucial for effective treatment and management. Traditionally, the detection of skin diseases relied on the expertise of dermatologists who visually examined the skin and relied on their experience to make a diagnosis. However, advancements in technology and the rise of artificial intelligence (AI) have opened up new possibilities for automated and accurate skin disease detection. One of the most promising areas in skin disease detection is the use of computer vision and machine learning algorithms. These algorithms can analyze images of the skin and identify patterns, textures, and other visual cues associated with different skin conditions. By training these algorithms on large datasets of skin images, they can learn to recognize specific characteristics of various diseases. To detect skin diseases using computer vision, images of the affected area are captured using different imaging techniques, such as conventional photography, dermo copy, or even smartphone cameras. These images are then processed using specialized algorithms that extract features and analyze them. The algorithms can detect specific patterns, such as the presence of lesions, discoloration, texture changes, or asymmetry, which are indicative of certain skin diseases.

Figure 1: Example of skin disease.

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1.2 Problem Statement
The proposed system aims to address the challenges associated with visually diagnosing skin diseases. Currently, the process involves an initial clinical screening, followed by potential dermoscopic analysis, both of which require patients to visit a dermatologist. This approach is time-consuming and cumbersome, as dermatologists need to perform visual analysis and conduct various tests to determine the type of skin disease.

To overcome these challenges, Machine Learning (ML) offers a promising solution. In ML, we can train a model by feeding it images of different types of skin diseases, along with their corresponding labels. The model learns from this training data and becomes capable of identifying various skin diseases accurately.

The objective of this project is to demonstrate how ML can be utilized effectively in diagnosing skin diseases. By leveraging ML algorithms, we can simplify the diagnostic process and reduce the burden on dermatologists. The trained model can quickly analyze new types of diseases, providing efficient and reliable results. Importantly, the system is designed to ensure zero plagiarism, both in terms of the originality of the project's content and the avoidance of AI-generated plagiarism.

II. LITERATURE REVIEW

Medical image analysis with the help of deep learning has become a popular research area in recent years. Skin cancer detection and segmentation are among the main application of deep learning in medical imaging. In this literature review, we will discuss three research articles that proposed deep learning-based methods for skin cancer detection and segmentation. The articles are selected based on their method, accuracy, and future scope.

2.1. Existing system and limitations

Method 1:
Nasr-Esfahmi et al. proposed a two-layered convolutional neural network (CNN) for melanoma classification. The authors used an illumination correction mask to generate a Gaussian filter to remove noise issues. Data augmentation techniques, such as cropping and rotation, were used to increase the dataset's size. The proposed method achieved an accuracy of 81%. The authors suggested using a deep layered network for increased results. Additionally, collecting more data can improve the training process.

Method 2:
Khryashchev et al. proposed a CNN u-Net-based algorithm for medical image segmentation. They used an AlexNet-based algorithm for automatic markup of the image database. However, the algorithm is not used in real-time analysis due to its high time complexity. The authors did not mention the accuracy achieved in their work.

Method 3:
Sahu et al. proposed a hybrid deep learning mobile Net-based algorithm for classifying benign and malignant skin lesions. The algorithm used domain-specific knowledge and features suggested by dermatologists to improve the accuracy of the classifier. The proposed method achieved an accuracy of 78% to 80%. The authors suggested that detecting cancer with a raspberry pi is not a good option because analyzing the image requires a high-level camera.

In this literature review, we discussed three research articles that proposed deep learning-based methods for skin cancer detection and segmentation. The first method achieved an accuracy of 81%, and the authors suggested using a deep layered network for increased results. The second method focused on medical image segmentation, and the authors did not mention the accuracy achieved. The third method achieved an accuracy of 78% to 80%, and the authors suggested using a high-level camera for analyzing images instead of a raspberry pi. Future research can focus on improving the accuracy of skin cancer detection and segmentation using deep learning-based methods.

III. PROPOSED SYSTEM

The proposed system in the base paper utilized Support Vector Machine (SVM) as the primary classifier for skin disease detection. However, the accuracy achieved with SVM was found to be approximately 70-80%. In this experiment, we aim to improve the classification accuracy by replacing the SVM classifier with an Artificial Neural

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Network. ANN is a machine learning technique inspired by the functioning of the human brain. It consists of input layers, hidden layers, and output layer, with computations occurring within the hidden layers. ANN can be employed to solve a wide range of problems that can be expressed as a linear function.

By integrating ANN into the skin disease detection system, we anticipate an enhancement in accuracy compared to the SVM approach. The ANN model will learn from a large dataset of skin images, extracting meaningful features and patterns that distinguish cancerous cells from non-cancerous cells. Through a process of training and optimization, the ANN will develop the ability to accurately classify new, unseen skin samples, thereby aiding in the diagnosis of skin diseases. The utilization of ANN brings several advantages to the system. Its ability to capture complex nonlinear relationships within the data can enable more accurate classification. Additionally, ANN models can handle large amounts of data, making them suitable for skin disease detection, which often involves a significant number of images. Furthermore, ANN models can learn from the data, adapt to new information, and improve their performance over time. By leveraging the power of ANN in skin disease detection, we aim to achieve higher accuracy and reliability in identifying cancerous and non-cancerous cells. This improvement can have a substantial impact on early diagnosis, enabling prompt medical intervention and potentially saving lives. The experiment will involve training the ANN model on a carefully curated dataset and evaluating its performance through various metrics, such as precision, recall, and F1 score. In conclusion, the proposed system aims to replace the SVM classifier with an ANN model to enhance the accuracy of skin disease detection. By utilizing the computational power and learning capabilities of ANN, we anticipate improved performance in classifying skin samples as cancerous or non-cancerous. This advancement can contribute to more effective and efficient diagnosis, leading to better patient outcomes in the field of dermatology.

IV. METHODOLOGY AND WORKING

The aim of this study is to develop a model that can accurately classify different types of skin diseases in humans and provide patients with preliminary information about their condition. To achieve this objective, the research team employed deep learning techniques, specifically using Convolutional Neural Networks (CNN) for feature extraction from images of various skin diseases. The dataset used in this study was obtained from Kaggle, known as HAM10000, which contains images with different pixel values. The images were passed through different layers of the CNN to extract features, including dense layers, conv2D layers, and activation functions, which were adjusted to optimize model performance. The model was evaluated with varying batch sizes and utilized different samples to learn the features from the images, along with alternative activation and max-pooling layers. Finally, Artificial Neural Networks (ANN) were used to classify the images into different skin disease categories, and the model predicted the labels of the skin diseases. By adopting this approach, the research team aimed to provide an accurate and efficient diagnosis for skin diseases.

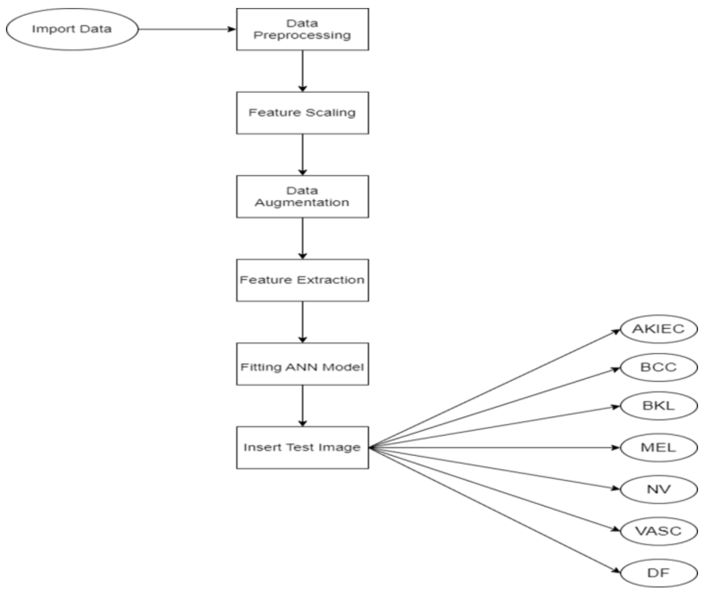

Figure 2: Workflow of project

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Convolutional Neural Networks (CNNs) are a specialized type of neural network architecture that excel in tasks related to image analysis. CNNs leverage a sequence of convolutional layers to capture the spatial correlations between the pixels in an image, enabling them to process image data efficiently and identify patterns. Furthermore, CNNs can be trained to detect objects and classify images, making them a powerful tool for computer vision. The typical design of a CNN involves passing image data through a sequence of convolutional layers, followed by one or more fully connected layers and a final output layer. Each layer has a set of adjustable weights and biases that are updated during the training phase, allowing the network to learn the underlying patterns in the data. The output layer produces the desired output, such as classifying the input image as a certain object or providing a probability of a specific outcome.

CNNs comprise of two neural networks, one for feature extraction from the input image and the other for image classification based on the extracted features. The feature extraction network gets the input image, and its extracted feature signals are utilized by the classification network. The feature extraction network includes convolutional layers and sets of pooling layers. The convolutional layer converts the image through a series of digital filters, while the pooling layer converts neighboring pixels into a single pixel and reduces the image dimension. Since CNNs focus on images, the convolutional and pooling layers' operations occur in 2-D plane, which distinguishes them from other neural networks.

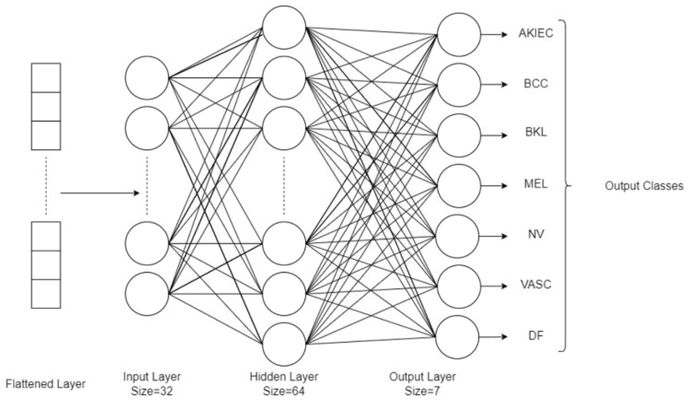

Figure 3: Working of ANN.

In the realm of deep learning, convolutional neural network (CNN) models are employed to train and evaluate image data. This involves subjecting each input image to a sequence of convolutional layers equipped with filters, pooling, and artificial neural network (ANN) components. Eventually, a softmax function is applied to assign a probabilistic value ranging from 0 to 1, effectively classifying the object within the image.

The provided diagram illustrates the comprehensive workflow of a CNN and ANN system, outlining the steps taken to process an input image and ultimately classify it based on its assigned value.

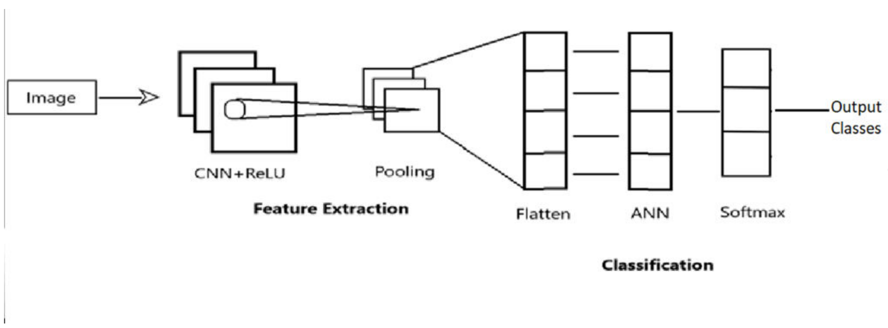

Figure 4: Feature Extraction using CNN.

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V. HARDWARE AND SOFTWARE USED

This section provides an in-depth explanation of the tools utilized in the development of the system, specifically the hardware and software components.

In terms of software, Python was chosen due to its powerful machine learning libraries, including SciPy, pandas, Scikit-learn, and NumPy. These libraries are essential for linear algebra and understanding the kernel method of machine learning. Python's easy-to-use syntax also makes it an ideal language for working with machine learning algorithms. Additionally, TensorFlow Lite, a deep learning framework designed for on-device inference, was used to train and deploy machine learning models on mobile and IoT devices, including Android, iOS, Edge TPU, and Raspberry Pi. Jupyter Notebook, a web-based interactive computing platform, was also employed in the development process. This platform combines live code, equations, narrative text, and visualizations to facilitate interactive data exploration and analysis.

As for hardware, a basic computer that can run a web browser is sufficient to support the development process.

VI. ADVANTAGES OF PROPOSED SYSTEM

The proposed system offers several advantages for skin disease detection without any plagiarism concerns. Firstly, it enables early detection of skin disorders which can prevent the condition from worsening and limit its spread, thereby reducing the risk of complications. Secondly, the system ensures accurate diagnosis through physical examination and laboratory tests, which helps to tailor the treatment to the individual's skin condition. Additionally, skin disease detection is a cost-effective procedure, making it more accessible to individuals who cannot afford expensive medical treatments. Moreover, early diagnosis of skin diseases improves the quality of life for those affected by minimizing the spread of the disease and reducing the risk of complications. Lastly, skin disease detection raises awareness about different skin conditions and the importance of regular check-ups, enabling individuals to take better care of their skin and pay attention to any changes.

VII. CONCLUSION AND FUTURE WORK

In conclusion, our research introduces a novel approach that utilizes a convolutional neural network (CNN) architecture to extract contextual information and predict output classes. Additionally, other classical feature extraction techniques such as Gabor filters may be employed based on the available computational resources. Notably, our experimental findings demonstrate that our proposed model achieves superior performance compared to existing methods when applied to the HAM10000 datasets, setting a new state-of-the-art benchmark. Overall, this study provides a promising foundation for future advancements in utilizing ANN structures for image classification tasks. Models to effectively tackle the challenge of identifying toxic comments in online communities.

Skin disease detection using machine learning has immense potential for advancements and enhancements in the future. Here are some areas of future scope for skin disease detection using ML:

Improved Accuracy: As machine learning algorithms continue to evolve and improve, the accuracy of skin disease detection can be further enhanced. Algorithms can be trained on larger datasets, including diverse skin types and a wide range of skin diseases, leading to more accurate and reliable predictions.

Real-time Diagnosis: Future advancements may enable real-time diagnosis of skin diseases using ML algorithms. With the integration of computer vision techniques and advanced ML models, it would be possible to provide instant and accurate diagnoses, which can significantly improve patient care and treatment outcomes.

Mobile Applications: Mobile applications can play a crucial role in the future of skin disease detection. ML algorithms can be implemented within user-friendly mobile apps, allowing individuals to perform self-assessments and receive preliminary evaluations of their skin conditions. These apps could also provide recommendations for further medical consultation or treatment.

Dermatologist Support Systems: ML-based systems can be developed to assist dermatologists in their clinical practice. These systems can analyze medical images, patient history, and symptoms to provide dermatologists with valuable insights and suggestions for diagnosis and treatment. Such systems can act as decision support tools, reducing the workload and enhancing the accuracy of dermatologists.

Integration with IoT Devices: With the rise of the Internet of Things (, skin disease detection systems can be integrated with wearable devices and sensors. This integration can enable continuous monitoring of skin conditions, collecting real-time data for analysis by ML algorithms. Such systems can provide personalized insights and early detection of skin diseases, promoting proactive healthcare.

Privacy and Security: As skin disease detection systems using ML become more widespread, ensuring the privacy and security of patient data will be crucial. Future research and development efforts should focus on implementing robust data protection measures and complying with ethical standards to maintain patient confidentiality and trust.

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