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SKIN DISEASES PREDICTION USING DEEP LEARNING TECHNIQUES

Thumu Swathi[1] , Dr.P.Srinivas[2]

[1]PG Scholar , Department of Computer Science and Engineering , Malla Reddy Engineering ,College(A), Maisammaguda,Secunderabad-500100, District -medchal, Telangana,India.
[2]Professor, Department of Computer Science and Engineering ,Malla Reddy Engineering ,College(A), Maisammaguda,Secunderabad-500100, District -medchal, Telangana,India.

Abstract-- Dermatological conditions have a substantial impact on the well-being of a large number of persons, since almost everyone experiences different types of skin disorders annually. Given the time-consuming and labor-intensive process of human analysis for these illnesses, along with the limited capability of current techniques to analyze specific types of skin diseases, there is a requirement for advanced computer-aided proficiency in the analysis and diagnosis of various skin diseases. This study lays out a procedure for real-time skin disease prediction that makes use of computer-assisted techniques including data mining algorithms and the CNN algorithm. When contrasted with other approaches, this strategy provides a more precise result.

Index-Terms: Dermatological Conditions,Computer-Aided Diagnosis ,Convolutional Neural Network (CNN),Skin Disorder Diagnosis,Medical Image Analysis.

1. INTRODUCTION

Artificial intelligence is replacing automation in several domains, including the healthcare industry. These illnesses have caused alarm in recent years because they appear suddenly and are complex, leading to greater risks to life. These dermatological illnesses are very contagious and need immediate treatment to avoid their spread. Unprotected exposure to high levels of ultraviolet (UV) radiation is a primary factor contributing to sickness. Benign skin lesions are less dangerous than malignant melanoma and may be successfully treated with proper medical intervention. However, malignant melanoma is the most severe kind of skin disease.The survey findings suggest that skin cancer is mostly seen on the trunk, lower limbs, and upper limbs. There is a significant population of patients between the ages of 30 and 60. In addition, those who are under the age of 20 seldom develop melanocytic nevi, malignancy, and dermatofibroma.The diagnosis of dermatological disorders is especially challenging due to the heterogeneity they display in various contexts.Dermatological diseases are the most prevalent among them, and they have a significant potential for transmission. If left untreated, these illnesses may develop into cutaneous cancers. Presently, the prevalence of skin cancer exceeds the combined frequency of new cases of lung and breast cancer. Studies suggest that around 20% of people may encounter the occurrence of skin cancer at some point in their lifetimes, therefore making the screening procedure more intricate. 1. Existing methodologies are limited to the examination of a singular kind of dermatological condition. 2. The evaluation and identification of several skin diseases need a higher level of computer-assisted proficiency.

2.PROBLEM STATEMENTS:

The process of diagnosing and forecasting skin disorders is a time-consuming one, including the investigation of the patient's medical records, doing a physical assessment, and conducting appropriate

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laboratory testing. The typical approach to conducting an examination and subsequent treatment requires a substantial quantity of clinical and histological features. The diagnosis and prediction of a disease get more challenging as the illness becomes more complicated and the number of symptoms grows. Thus, a sophisticated computer-assisted diagnosis and identification method is introduced. Due to the laborious nature of human study with the present technology, only certain types of skin diseases are currently being examined. As the complexity and abundance of the disease's features increase, the task of detecting and predicting the sickness becomes more challenging. Presently, the examination of such disorders in persons necessitates a substantial investment of time and exertion.

PROPOSED METHODOLOGY:

A neural network is a machine learning technique that allows a computer to acquire knowledge by incorporating fresh data. Convolutional neural networks (CNNs) are very advantageous in the domain of image recognition for the explicit task of assessing visual imagery and are often used in the categorization of images. The algorithm receives three categories of skin illness photographs as input and offers the probability that the input corresponds to a certain category as output.CNN has emerged as the favored framework for resolving any image-related problem. The main advantage of CNN, in contrast to earlier models, is its capacity to independently detect important features without any human intervention.
It provides a higher level of accuracy in comparison to other techniques.The goal is to optimize the process of detecting and treating skin disorders via automation, while also offering a cost-efficient method to treating skin diseases.In order to accelerate the process of identifying certain dermatological diseases.

3 .SYSTEM SPECIFICATION

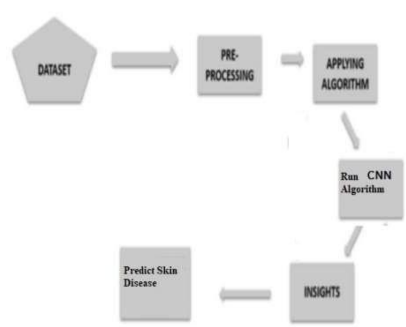

Figure .1 System Process

Data Collection:

Images: An extensive compilation of skin lesion pictures is assembled, including various types of imaging such as clinical photographs, dermoscopic images, and histological images.

Annotation: Dermatologists or certified professionals provide commentary on photos, with comments that specify the precise skin condition.

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Preprocessing:

Normalization: Images are standardized to provide consistent lighting and color balance.

Segmentation: Techniques are used to distinguish the skin lesion from the surrounding skin, which may include the deployment of additional Convolutional Neural Networks (CNNs) specifically trained for segmentation purposes.

CNN Model Architecture:

Convolutional Layers: These layers gather data from the pictures and develop the capability to recognize patterns like edges, textures, and shapes that are specific to certain skin conditions.

Pooling Layers: These layers decrease the spatial size of the representation, resulting in a reduction in parameters and computational load in the network.

Fully Connected Layers: The layers combine all the characteristics to perform the final classification procedure.

Training:

Backpropagation: The network is trained using the backpropagation methodology, which reduces the discrepancy between the predicted output and the actual label by using optimization techniques like stochastic gradient descent.

Regularization: Dropout and weight decay are used as strategies to alleviate overfitting, hence ensuring the model's capacity to generalize well to unfamiliar, unseen data.

Evaluation:

Validation Sets: A portion of the data is designated as a validation set to refine hyperparameters and reduce overfitting.

Test Sets: A number of special tests and metrics are used to evaluate the efficacy of a model, including accuracy, sensitivity, specificity, and area under the curve (AUC).

Deployment:

Clinical Integration: CNN models may be integrated into clinical procedures, either as standalone tools or as parts of a more extensive decision support system.

Mobile Applications: Convolutional Neural Networks (CNNs) may be deployed on portable devices, enabling easy access and perhaps enabling prompt detection of skin illnesses.

Challenges and Considerations:

Data Imbalance: Imbalanced skin disease statistics may demonstrate an inequality in the occurrence of various ailments, with some problems being more widespread than others. Techniques like as oversampling, undersampling, or using class-weighted loss functions may successfully address this

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issue.

Generalization: To be useful in real-world applications, it is crucial to guarantee that the model has strong generalization skills across different populations, skin tones, and photo capturing conditions.

Interpretability: Although CNNs possess significant computational capabilities, they are often seen as opaque or inscrutable. Initiatives are underway to enhance the transparency and comprehensibility of the decision-making process for clinicians.

Ethical and Legal Considerations: When using Convolutional Neural Networks (CNNs) in clinical settings, it is of utmost importance to carefully address and resolve concerns pertaining to privacy, data security, and adherence to regulatory requirements.

Examples of CNN Architectures Used:

VGGNet: VGGNet is highly recognized for its simplicity and comprehensiveness, making it a popular benchmark for many image classification tasks, including the identification of skin conditions.

ResNet: Residual Networks (ResNet) use connections that skip to facilitate the training of very deep networks, allowing them to learn more complex characteristics.

Inception: The Inception architecture, namely InceptionV3, was chosen because to its ability to gather features at both the detailed and broad levels.

DenseNet: Densely Connected Convolutional Networks are beneficial for medical image processing since they facilitate feature reuse and limit the number of parameters needed.

Future Directions:

Advanced Architectures: Researchers are now exploring advanced Convolutional Neural Network (CNN) architectures and hybrid models that combine CNNs with other kinds of neural networks, such as (RNNs) or Transformer models to improve performance.

Multimodal Learning: Data fusion is the process of integrating information from several sources, such as clinical data, genetic information, patient history, and imaging data, to enhance the accuracy of medical diagnosis.

Explainable AI: Developing models that not only provide accurate predictions but also give explanations for their findings, a crucial factor in instilling trust and acceptance in the medical domain. In summary, Convolutional Neural Networks (CNNs) have become a vital element of the diagnostic tools used for the detection of skin diseases. They possess the capacity to improve precision, accelerate the diagnosis process, and provide access to diagnoses of expert-level quality in areas with limited dermatological resources. However, it is essential to carefully assess the challenges and ethical implications to ensure the safe and effective use of these technologies in therapeutic contexts. The Importance of Deep Learning

Dermatology :Accuracy: Deep learning models may attain equivalent or even surpassing accuracy to that of dermatologists in identifying certain skin disorders, such as melanoma.

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Efficiency: Automated systems has the capacity to rapidly analyze large volumes of skin images, hence providing immediate diagnostic assistance.

Accessibility: These systems can be deployed in mobile apps, making dermatological diagnostics accessible in remote or underserved areas.

Image Collection: The collection of dermatological pictures is obtained from several sources, including clinical environments, public databases, and contributions from patients.

Annotation: Dermatologists categorize the photographs, creating a dataset combining images with specific skin conditions.

Data Augmentation: Rotating, rotating and zooming are some of the methods used for improving the dataset's diversity and the model's robustness.

Model Architecture Convolutional Layers: These layers have the function of detecting and classifying components inside images. The process starts with the identification of basic edges and gradually advances to the recognition of complex patterns, such as textures and shapes that are linked to certain skin conditions.

Pooling Layers: These layers have the function of detecting and classifying components inside images. The process starts with the identification of basic edges and gradually advances to the recognition of complex patterns, such as textures and shapes that are linked to certain skin conditions.

Fully Connected Layers: The input is initially flattened by the pooling and convolutional layers, and then passed through fully connected ones. These layers provide predictions based on the characteristics that have been extracted.

Output Layer: A softmax function is often used in the output layer of a classification task to assess the probability of each skin condition.

Training the Model: Commonly, categorical cross-entropy serves as the loss function for classification issues.

Optimization: Optimizers like Adam or SGD are used to adjust the weights of the model with the aim of minimizing the loss function.

Regularization: Techniques like as dropout, which randomly remove neurons during training, help to reduce overfitting and improve the model's capacity to generalize to unexpected input.

Model Evaluation:Accuracy: The precision of the model's forecasts. Precision, Recall, and F1 Score: These measures provide a more thorough evaluation of the model's efficacy, especially when working with imbalanced datasets, such as those with a limited number of images representing uncommon illnesses.

Confusion Matrix: This tool helps visualize the model's performance by showing how many times each condition is correctly or incorrectly predicted. AUC-ROC Curve: For binary classification tasks, this curve helps evaluate the model's ability to distinguish between two classes.:Applications of Deep

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Learning in Skin Disease

Melanoma Detection: CNNs are widely used to distinguish between benign moles and malignant melanoma, one of the deadliest forms of skin cancer.

Multi-Class Classification: Deep learning models can classify images into multiple skin conditions, such as acne, psoriasis, eczema, and others.

Teledermatology: Mobile apps powered by deep learning can provide users with preliminary diagnoses based on images taken with their smartphones.

Challenges and Considerations:Data Diversity: Ensuring that the dataset includes a wide range of skin tones, ages, and conditions to avoid bias and improve the model's generalizability.

Interpretability: Making the decision-making process of deep learning models understandable to clinicians to build trust in AI-driven diagnoses.

Regulation and Validation: Ensuring that models meet regulatory standards and are validated through rigorous clinical trials before deployment in real-world settings. Future Directions:Explainable AI: Developing methods to explain the decisions made by deep learning models to enhance trust and adoption in clinical settings. Integration with Electronic Health Records (EHR): Combining image-based diagnosis with patient history and other medical data for more comprehensive assessments. Continual Learning: Building models that can continuously learn from new data, improving their accuracy and relevance over time.

4. IMPLEMENTATION:

MODULES:

We have now effectively developed both data mining and ensemble techniques. To facilitate the training of these algorithms, we have included the following modules:Partition the dataset into distinct segments for the purposes of training and testing: After applying image processing techniques, the dataset was split into an 80% training set and a 20% testing set. 80% of the trainset was used to train Ensemble and data mining algorithms. Afterwards, we used the remaining 20% of the test data to evaluate the trained model's accuracy, precision, recall, and F-score.

Implement Data Mining methodologies: Using this module, we have effectively taught several data mining approaches, such as the CNN Algorithm.

Accuracy Comparison Graph: All the various algorithms' FMEASURE graphs, as well as their accuracy, precision, and recall, are shown in this module.

Predict Skin Disease: In order to predict skin diseases, this module will be used to send test results to a data mining algorithm.

Algorithms:

Convolutional Neural Network: An prominent machine learning model that mimics the way the human

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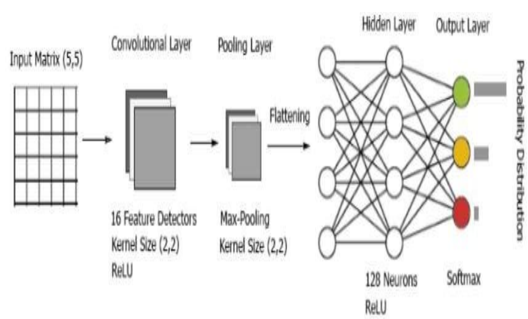
visual cortex works is a Convolutional Neural Network (CNN). Due to its outstanding performance in image and pattern recognition tasks, the CNN has become quite popular in several applications [23]. Due to its capacity to extract important local features from input data, CNN is exceptionally well-suited for traffic status prediction. Given the importance of adjacent values of traffic status in both geographical and temporal dimensions, this is of the utmost importance. A CNN architecture consisting of a convolutional layer, a max pooling layer, a fully connected layer with a dropout of 20%, and an output layer was used in this research. The proposed model's overall architecture is shown in Figure 3. The Keras toolkit, along with the TensorflowTM back end, was used to create the model.

1) Convolutional Layer: Feature extraction from the input matrix is the goal of this layer, which systematically traverses each feature detector (kernel). The amount of kernels used determines the amount of characteristics that may be extracted. A total of sixteen 2 by 2 kernels were used for this experiment. An activation function will be applied to the output of the convolutional layer in order to bring nonlinearity into the model. Since Rectified Linear Units (ReLUs) do not compress the input and enhance training speed, they are suggested as the activation function to be employed for this purpose [23]. The ReLUs function is expressed in Equation (1).If x is bigger than zero, then the function f(x) is defined as f(x). f(x)=max(0,x)



2) Figure .2 Proposed CNN Model

2) Max-Pooling Layer: Convolutional neural networks (CNNs) include a pooling layer that strengthens features and decreases the amount of trainable parameters in order to better handle noisy or distorted input. Max-pooling outperforms other pooling methods in capturing data invariances, which is why it is used extensively in a number of research investigations [25, 26]. In max-pooling, the matrices produced by the convolutional layer are examined, and the one with the highest value in each region is selected. By applying this method to the selected values, a reduced matrix is produced. Following the recommendation of Ma et al. [22], this work used max-poolings with 2 by 2 dimensions for the pooling layer. Here is the formula for max-pooling using a 2 by 2 filter: In a given matrix, the term "ypooling" describes the situation where the values at the i and j coordinates are the maximum, represented as xij. The values of i and j may range from 1 to 2. To feed the flattened pooling layer outputs, the fully-connected layer uses them as input nodes. Every connected connection in an MLP network multiplies the input nodes by a predetermined weight. Each buried layer node's input values will be added together using an activation function. After that, it will be sent to the output layer. In this study, the activation function for a 128-neutrino hidden layer was the Rectified Linear Unit (ReLU). A 20% dropout rate is used to tackle the issue of overfitting [27]. Assigning a value of 0 to certain activations at random is known as "dropout," and it encourages the model to look for other ways to classify images instead of

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depending on specific features. Successful image classification model AlexNet demonstrated the efficacy of this method [28]. Using the input data and the learnt patterns and connections inside the network, the last layer of a neural network, called the output layer, is responsible for providing the ultimate predictions or outputs. In this layer, each node receives data from every node in the hidden layer and uses an activation function to produce the model's final output. One way to look at the supplied data is as a categorical issue with three labels, as it comprises three distinct variables. Therefore, the Softmax function is the best choice for the output layer. A categorical distribution, representing a probability distribution across numerous alternative outcomes, is generated using the softmax function. After determining the loss using the category cross entropy function, the training procedure continues by backpropagating to adjust the link weights.

5.RESULTS:

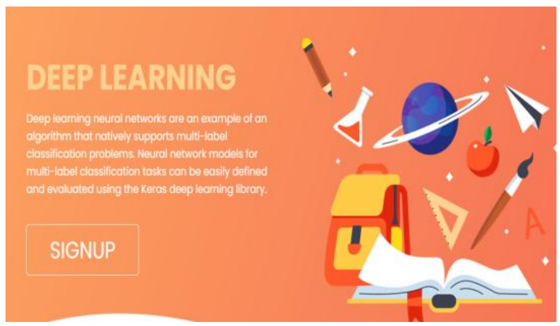

Figure.3 Home Page

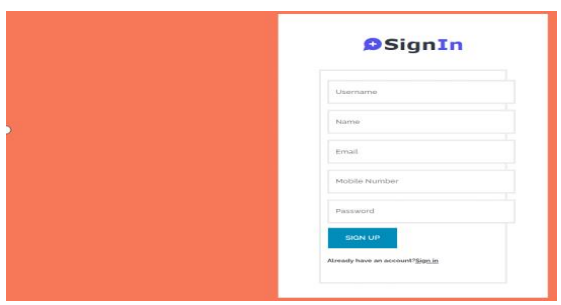

Figure.4 Registration Form

Figure.5 SignIn Form

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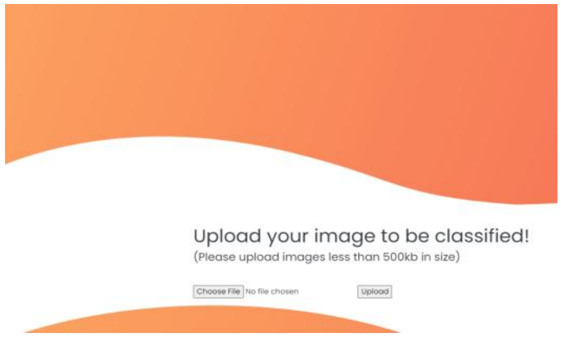

Figure.6 Upload form

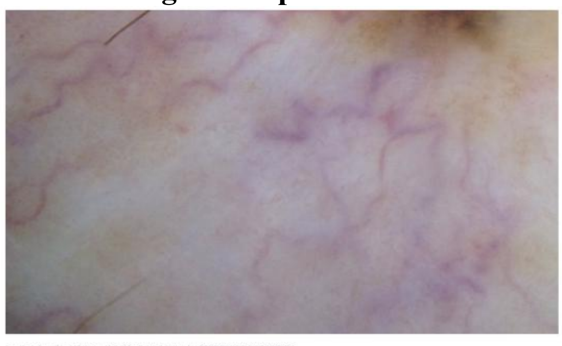

Figure.7 Result

6. CONCLUSION

The proposed approach showcases the capacity to detect skin illnesses with positive results by combining computer vision and machine learning techniques. It has the capacity to aid persons worldwide and enable efficient jobs. The instruments used are readily available and may be utilized by the user, allowing for the installation of the system at no cost. The program has been intended to be lightweight and is compatible with PCs that have modest system specifications. Furthermore, it has a simple and intuitive user interface to optimize user convenience. The deployment of the deep learning algorithms was accomplished well.

7. REFERENCES

[1] Damilola A. Okuboyejo, Oludayo O. Olugbara, and Solomon A. Odunaike, "Automating Skin Disease Diagnosis Using Image Classification," Proceedings of the World Congress on Engineering and Computer Science 2013 Vol II, WCECS 2013, 23-25 October, 2013, San Francisco, USA.

[2] R. Yasir, M. A. Rahman and N. Ahmed, "Dermatological disease detection using image processing and artificial neural network," 8th International Conference on Electrical and Computer Engineering, Dhaka, 2014, pp. 687-690, doi: 10.1109/ICECE.2014.7026918.

[3] Ambad, Pravin S., and A. S. Shirat, "A Image Analysis System to Detect Skin Diseases," IOSR Journal of VLSI and Signal Processing (IOSR-JVSP), Volume 6, Issue 5, Ver. I (Sep. - Oct. 2016), PP 17-25.

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

[4] R S Gound, Priyanka S Gadre, Jyoti B Gaikwad and Priyanka K Wagh, "Skin Disease Diagnosis System using Image Processing and Data Mining," International Journal of Computer Applications 179(16):38-40, January 2018.

[5] V. B. Kumar, S. S. Kumar and V. Saboo, "Dermatological disease detection using image processing and machine learning," 2016 Third International Conference on Artificial Intelligence and Pattern Recognition (AIPR), Lodz, 2016, pp. 1-6, doi: 10.1109/ICAIPR.2016.7585217.

[6] M. Shamsul Arifin, M. Golam Kibria, A. Firoze, M. Ashraful Amini and Hong Yan, "Dermatological disease diagnosis using color-skin images," 2012 International Conference on Machine Learning and Cybernetics, Xian, 2012, pp. 1675-1680, doi: 10.1109/ICMLC.2012.6359626.