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Skin Disease Detection and Recommendation System using Deep Learning and Cloud Computing

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***Abstract*—The main objective of this research is to develop an application based on Deep learning, Computer vision and cloud computing that detects the different kinds of skin diseases caused by different types of viruses, Bacteria, Fungus and Environment. This study has also developed and integrated a recommendation system, which recommends the medicines and care taking process for a particular disease. The application also suggests preventive methods for different kinds of skin infections. This study used an ensemble of convolution neural networks (CNN) with generative adversarial network (GAN) and Computer vision for construction of the model. Further, Amazon Personalize is used to build recommendation system in the proposed web application. The proposed application detects the disease based on symptoms, pictures, and videos of infected skin area. The application will be helpful for dermatologists and common people to perform early detection and prevention of skin diseases in India. This study also compared the accuracy of ensemble of convolution neural networks (CNN) with GAN and other algorithms like CNN. In comparison of accuracy, this study found that the Ensembles of CNN with GAN give best results for the proposed dataset.**

***Keywords*— Convolutional neural network, Generative Adversarial Networks, Cloud Computing, Amazon web services personalize, Deep learning, Computer Vision.**

I. Introduction

Deep transfer learning applied in medical imaging during the past few years for classification and segmentation, improving diagnosis accuracy. In order to feed the result of one layer as input to the following sequential layers, state-of-the-art deep learning algorithms are developed utilizing neural networks structured in layers, with the first layer extracting basic picture information like edges, colors, etc. Hence, as the number of layers increases, so does the complexity of learning. Deep learning is a technique that is autonomous and has numerous advantages over conventional machine learning algorithms. However, for improved performance, it needs a huge amount of annotated data; as a result, the size of the public datasets that are currently available is limited [1]. Many skin conditions pose a serious health risk to millions of people globally. Efficient treatment and management of skin diseases depend on early detection and precise diagnosis. manners Iven the complexity and diversity of lesions, and the limited information and expertise of healthcare experts, it can be difficult to diagnose skin disorders accurately and in a timely manner. Automating skin disease identification and categorization using computer vision and machine learning techniques has become more and more common as a solution to this problem. These methods make it possible to analyses skin lesion photos and extract useful aspects that can help with the precise identification of skin diseases.

Several branches of computer science have emerged during the past several decades, showing promise for aiding diagnostic procedures. One such subject is artificial intelligence (AI), which is focused on automating the diagnosis process by creating sophisticated algorithms and has the potential to outperform human experts. Researchers from Italy, the United States, and France used an AI system to identify and categories malignant from benign skin lesions by putting more than 1 million skin lesion photos into a convolutional neural network. This research confirmed the efficiency of the AI system (CNN). Human classification specialists performed with an accuracy of 86.6% compared to the AI system's classification accuracy of 95%. One subtype of AI that automates processes by using input data in the form of images is computer vision. The AI system makes use of a variety of methods where algorithms iteratively learn from data [2,3].

In computer vision, Convolutional Neural Networks (CNN) are regarded as the most widely used deep learning technique. It is neural networks with layers that are organized hierarchically, in the result of one layer feeding into the input of the next layer. Here, the initial layer extracts the most fundamental aspects of the picture, such as its edges, colors, and so forth, and as more layers are added, the complexity of the extraction grows. CNNs are capable of autonomously learning and extracting features with sufficient and appropriate training. In a computer vision the application, CNN receives an input picture, prioritizes various features in the image by updating weights and biases, and then distinguishes between them. The conventional augmentation serves as a benchmark technique to enhance CNN's performance and to provide a comparative study with other techniques. By performing a straightforward geometric transformation on the initial samples, it can be used sparingly. This type of transformation encompasses shearing, flipping, scale shifts, rotations, and translations.

With the aid of machine learning, Amazon Personalize enables developers to swiftly create and distribute customized suggestions and excellent user segmentation (ML). You can offer the correct customer experience just at the right moment at the correct location by using Amazon Personalize, which can be customized to meet your specific needs.

One of the newest breakthroughs in recommendation system technology is deep learning. Deep neural networks have achieved outstanding results over the past few years in a variety of challenging machine learning tasks, including natural language processing, computer vision, and speech recognition. Deep learning for recommendation systems was initially adopted by the community of recommender systems very slowly, but in 2019, it gained a lot of traction [13].

I think that a deep learning tutorial will contribute to the topic's increased popularity. Medicine suggestions, treatment suggestions, and session-based recommendations are some notable recent application fields. The tutorial's purpose is to stimulate research into deep learning approaches for recommender systems and to encourage the use of these techniques in recommender systems.

II. RELATED RESEARCH

The difficulty of deep learning, which is an intuitive process, rises as the number of layers does. It is recognized as a mature technology for medical diagnostics because of its excellent performance. Deep learning has recently made a substantial contribution to issues with skin lesion classification. Yet, a small data set makes it more difficult to conduct potentially ground-breaking deep learning research in medical diagnostics. One reason is that the deep learning algorithm is dependent on the size of the training data because it needs billions of parameters and a lot of labelled data to learn [26]. When only a small amount of data is utilized to train a deep learning model, the system devotes a significant number of resources to that task, producing over [4,5].

An overfitting problem is when a model cannot generalize to new data. Several studies have been conducted to find solutions to the problems caused by the scarcity of data when training deep learning models. It consists of methods such as ensemble of classifiers, transfer learning, and augmentation. The sections that follow give an overview of current methods and associated research in the topic of skin lesion classification [6].

In addition to harming physical health, skin conditions can also cause psychological issues, particularly in individuals whose faces have been injured or even deformed. Most people can get convenient clinical photos of their facial skin condition using smart gadgets. Convolutional neural networks (CNNs) have on the other hand, outperformed humans in the imaging area by a wide margin. As a result, This article investigated various CNN algorithms for classifying facial skin diseases based on clinical photos. First, we created a dataset with 2656 face images from Xiangya-Derm, which contains, as far as we know, China's largest medical image data set of skin diseases. These diseases include seborrheic keratosis, actinic keratosis, rosacea, lupus erythematosus, basal cell carcinoma, and squamous cell carcinoma [8,9].

To categories these disorders in the dataset, we conducted research using five network methods and compared the outcomes. When comparing the performances, it was found that almost all structures had greater average accuracy as well as recall for the models that applied transfer learning. Particularly dangerous and frequently contagious include Melanoma, acne, and impetigo [12].

When found early enough, some skin conditions are curable. The main issue with it is that only a skilled dermatologist can identify and categories such diseases. Sometimes medical professionals misclassify a patient's illness and give them the wrong drugs as a result. A skin cancer detection system that utilizes image analysis and deep learning methods is proposed in our project [14].

III. PROPOSED MODEL

The ensemble of CNNs uses the same conventional ensemble method idea. Individual CNN classification algorithms are used as the groups of classifiers in this instance rather than decision trees. To achieve the final classification in this case, we train numerous networks and average the probabilities given by each individual classifier. Instead of creating a single CNN for classification in the first stage, we create an ensemble of CNNs. After this, we train an ensemble of CNNs independently using datasets that have been expanded using both conventional and GAN-based augmentation. The final decision is made by a meta classifier, which averages or adds the votes of all the classifiers to make the best prediction. An ensemble of classifications is an algorithm for learning where each group of classifiers outputs its decision (vote) [7].

The selected approach consists of two distinct steps: building an ensemble of CNNs and training them on a larger dataset. Here, a group is built by modifying the training case to produce many theories. The algorithm is trained multiple times using various subsets of training data. Due to its unpredictable nature, CNN is a good candidate for such a construction technique. The choice of 5 to 10 CNN networks to use for an ensemble has been taken into consideration due to training limitations like computational costs, time consumption, etc. Conventional ensemble techniques like random forests typically give over 30 decision trees.

Where the amount of weighted error is determined, weights are changed, and the prediction is returned in each iteration i. Each classification in this case is a theory regarding the actual function f. In other words, hi stands for the hypothesis that when a classifier encounters a new case "x," it returns the true function f, and the hypothesis universe in an ensemble stands for a space of numerous hypotheses. Weights are updated until the most effective hypothesis is found, and the least amount of error is observed. Jensen's inequality is used in the section to illustrate how the averaging prediction across multiple networks operates. On a larger data set that includes original samples, conventionally augmented samples, and GAN generated samples, we build an ensemble of five CNNs. The ensemble searches the space of all conceivable classifiers once there is sufficient training data.

A. *Training an Ensemble of CNN*

Multiple networks are trained concurrently using a four loop to train five networks in our case, resulting in a serialized model at the end of each iteration. First, five different CNN models are constructed using the proposed CNN architecture as described below. Models are then loaded and trained on an enlarged dataset of skin lesions using a stochastic gradient optimizer and binary cross entropy as the cost function [8].

```
# loop over the number of models to train
for i in np.arange(0, args["num_models"]):
        # initialize the optimizer and model
        print("[INFO] training model {}/{}".format(i + 1,
                args["num_models"]))
        opt = SGD(lr=0.01, decay=0.01 / 40, momentum=0.9,
                nesterov=True)
        model = cancernet.build(width=64, height=64, depth=3,
                classes=2)
        model.compile(loss="binary_crossentropy", optimizer=opt,
                metrics=["accuracy"])
```

Fig 1: Code for Ensembles of CNN

The models are trained for 45 epochs with 64 batch sizes. Because 5 CNN models are trained sequentially, training takes five times as long as training and one CNN model. An ensemble is assessed on the test dataset, with each model producing two probabilities for each category label for each data point in the test dataset, i.e., each model producing a prediction array of size 100X2. (Test dataset has 100 images). The forecasts from all models are then aggregated by looping through each individual model. After looping through five models, the new prediction arrays have five models with two class label probability for 100 test data items.

In numerous applications, convolution neural networks have demonstrated their superiority as a model for deep learning. The CNN models have consistently demonstrated their proficiency while handling the massive data sets to find features and make predictions. In the vast majority of applications, a single CNN model is used. There is always the possibility of using an ensemble learning strategy along with a set of CNN models for the same tasks. We talked about the individualization of ensemble methods of instruction in one of our papers and how it has improved their effectiveness. Let's use CNN models to fine-tune this assembling strategy now. If it works, it can be used for applications where the CNN models have performed poorly in terms of accuracy [10, 15].

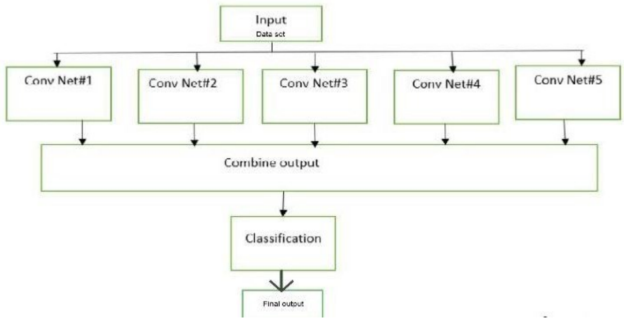

Figure 2: Ensemble of CNN

IV. IMPLEMENTATION

We developed a Application with best Algorithm for Selected data using deep learning and Computer vision. We integrated recommendation system developed using AWS personalize. The System generates individual responses which contains the level of disease, Precautions and Medication. The application is divided into 3 modules.

A. *Module 1 : Detection System*

The first module consists of a Detection System. The user needs to upload the pictures and videos of the infected area with symptoms. The Detection system predicts the type of disease based on the given input data.

B. *Module 2 : Recommendation System.*

The Recommendation System provides the prior medication details and precautions. The recommendation system is developed on AWS personalize.

C. *Module 3 : Blogs*

The third module is a informative section which provides the information and weekly blogs. The preventive information is really help for people to avoid and face different skin problems.

V. RESULTS AND ANALYSIS

The utilized accuracy and sensitivity as performance indicators to assess the effectiveness of classifiers for melanoma detection in our suggested models. AC and SN performance measures were utilized to assess the classifier's effectiveness. The confusion matrix was used to calculate the metrics. The classifier uses all test photos for binary classification and predicts whether each image will be positive or negative using the four scenarios described below:

1. True Positive (TP): A true positive is a prediction that comes true and is positive.
2. False Positive (FP): A false positive is a prediction that is correct but positive.
3. genuine Negative (TN): A genuine negative prediction is one that is accurate yet unfavorable.
4. False Negative (FN): This term refers to an incorrect and negative prediction.

The accuracy of a prediction is measured as the proportion of all right predictions to all the images in the dataset. The sum of the total number of accurate predictions is calculated. Using a formula, AC is written as

$$AC = T P + T N \ / T N + T N + F N + F P$$

Sensitivity (SN) is defined as the proportion of accurate positive predictions to all positive forecasts. The sum of TP and FN determines the overall number of positive predictions, hence the formula for SN is as follows:

$$SN = T P/ T P + F N$$

The chosen model combines a CNN ensemble with GAN-based augmentation. However, for comparison, we have chosen various examples where GAN-based augmentation was successful in enhancing CNN performance. Improved efficiency of CNN is true aim for the classification models.

We developed five CNN classifiers independently on the final numbers of 8000 images to assess the efficacy of an ensembles of CNN classifiers. Each individual model can only perform at a level of 89–90%, but when an ensemble technique is applied, the performance marginally rises to 97%. This finding demonstrates the possibility that the classification performance could be enhanced by combining five CNN classifiers into a single meta-classifier.

In comparison to CNN the results of the Process and research demonstrate that Ensembles of CNN with GAN did quite well. The Accuracy and sensitivity of CNN classifier is 89 and 85. The accuracy and Sensitivity of ensembles of CNN classifiers with GAN is 97 and 93. The ensembles of CNN classifiers with GAN performed well for our data set. We used the approach of ensembles of CNN classifiers with GAN in our application development.

s.no	Model	Accuracy	Sensitivity
1	CNN	89	85
2	Ensembles of CNN with GAN	97	94

Table 1: Accuracy and Sensitivity table.

A. *Methods for achieving High accuracy.*

The utilized K-Fold Cross-Validation, a technique for dividing your information into the training set and verification set. Stone M originally mentioned this approach in 1978. K-Fold Cross-Validation divides the photos into K equal-sized pieces. Then, you train your model K times using various training and validation sets. Our training data are divided into k successive folds by the Fold object. You select the number of folds when making the object. After that, the object returns two arrays when you call split on it. Indexes from the data we used for training are contained in the first array. Indexes from the training information are included in the second array for validation.

Training a model using every training and validation set, iterating over all folds. Every model receives a different filename. When we save the model with the smallest loss, we use that filename. The history object returned by TensorFlow's fit method is then added to an array. At the conclusion of training, we use the resulting array to generate a diagram of each fold.

Through the training and blending of different models, ensemble learning aims to enhance predictions. Ensemble learning is what we did earlier with K-Fold Cross-Validation.

VI. CONCLUSION

Using computer vision and Deep learning approaches, the suggested system demonstrates promising results in the detection of the skin illness. It can be used to carry out some useful activities as well as to assist people from all around the world. The system can be deployed for no cost because the tools are free to use and accessible to the user. The created application is portable and can be used on machines with basic system requirements. For the comfort of the user, it also features a straightforward user interface. Deep learning and image processing methods were successfully used. We also Implemented the Recommendation system successfully by using AWS Personalize. We also learnt the integration of Deep learning and Cloud computing in Building web applications. A group of CNNs can boost classification performance by 4 to 8%. Using an ensemble of CNNs with the augmentation methods can significantly enhance overall performance.

In this study, deep learning algorithms are used to create a model for the prediction of skin illnesses. It has been discovered that utilizing ensembling characteristics and deep learning, we can increase accuracy and predict a greater number of diseases than we could with any of the previous models. As previous models developed for this application could only indicate a maximum of eight skin conditions with a maximum level of 97.5% accuracy. We can predict up to 40 diseases with a greater accuracy level of 97% by adopting a deep learning algorithm. This demonstrates the enormous potential of deep learning algorithms for diagnosing skin diseases in the real world. The accuracy can be further improved by using even more advanced hardware and software, together with a very large dataset, and the model can be utilized for clinical experiments because it doesn't involve any intrusive procedures. As it will speed up therapy and diagnosis, further study can be done to standardize this model as a strategy for identifying skin diseases early on.

Skin illness identification is based on clinical knowledge and visual perception. However, computerized skin-image analysis systems do not have the subjectivity, lack of accuracy and repeatability that characterize human visual diagnosis. These systems make it possible for less skilled operators to screen prospective patients. The visual presentation of skin illness is more pronounced when compared to other diseases or applications, such as industrial defect diagnostics, which facilitates the major usefulness of deep learning in recognizing images with visual sensitivity. Dermatology may develop into one of the medical specialties best suited for telehealth and machine learning (AI) via the study of huge, comprehensive images. In the future, deep learning with some other technology like quantum computing might be able to supplement or possibly take the position of dermatologists in the detection of skin diseases using imaging techniques.

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