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Original Article

Skin Disease Ensemble Classification Using Transfer Learning and Voting Classifier

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Abstract *- Recognizing the signs and symptoms of various skin disorders helps make a clinical diagnosis and administering appropriate therapy much easier. Based on a multi-stage feature-processing technique, this study provides a multi-stage feature-processing, and machine learning classifier ensembles approach to skin disease identification. The classifier includes both the Voting Classifier and the Transfer Learning application. The architecture proposed is based on the concept of transfer learning and includes a large number of previously trained deep convolutional neural networks. It is also placed between the post-transfer learning process and the feature selection strategy, assisting us in automatically determining which features are most relevant for prediction and hence which features are most significant for prediction. Following the extraction of the deep features, the classifiers do data analysis. After a large number of classifiers have been deployed, the voting classifier makes predictions about the image's content. This set of deep features is fed into a huge number of machine learning classifiers, which are then used to forecast the final result. The research uses ISIC's publicly available skin image datasets to better understand how different types of pre-trained models, machine learning classifiers, and deep feature extractors differ. A study of big skin datasets shows that combining deep features with a voting classifier improves overall performance in the skin classification job.*

Keywords — *deep learning, ensemble learning, skin disease classification, machine learning, transfer learning, voting classifier*

I. INTRODUCTION

Skin problems are less common than other ailments, yet they are nevertheless prevalent. Skin illnesses can be caused by a variety of factors, including fungal infection, bacteria, an allergy, or a virus. Skin sores can change the texture or color of the skin. According to the National Psoriasis Foundation, eczema, psoriasis, and several other skin ailments are examples of skin disease that usually causes persistent, contagious, and occasionally advance to skin cancer. It is critical to recognize and treat skin infections as soon as possible in order to prevent the progression of these illnesses. Diagnosis and treatment are time-consuming and expensive, but they can be avoided with appropriate diagnosis and treatment. The general public is typically unaware of the many types and stages of skin disease. The long amount of time in which indicators of skin issues may not appear gives the condition more chance to progress. People are often unaware of medical issues, which is why this is happening. In some circumstances, doctors will request additional laboratory testing to help identify the skin condition.

Despite the fact that most people do not consider skin to be an organ, it is the largest organ the researcher has. As a result, it is critical that the researcher take proper care of it. Even with proper skincare, the researcher will develop a variety of skin disorders. While some of the disorders demand the use of outside medical care, others are minor. Acne, hives, sunburn, Rosacea, eczema, herpes zoster, and psoriasis are a few of the more prevalent skin problems seen by doctors.

Some recent study has propelled scientific curiosity to unprecedented heights. Artificial intelligence has greatly aided our understanding of the human body. Artificial intelligence (AI) has recently gained traction. All three AI components are in high demand right now: machine learning, artificial neural networks, and deep learning (shown in Fig1). It will be common in all fields of biology in the near future. The primary reason for this is that the answer is not linear. Because scanning-based sickness detection does not necessitate any special methodologies, DNN is the preferred method. Disease detection relies on actual medical data rather than algorithms. With limited financial resources, a huge number of health care providers are devoting themselves to modernizing outmoded facilities and aging systems. In healthcare administration, a combination of deep learning architectures and neural networks is used to deliver cost savings, more specific assessment, and intelligent decision-making. Artificial intelligence and neural networks have been used as an additional strategy in the treatment of many types of cancer and cardiology. A team member from ANN Health Services Company claimed that their healthcare systems include disease diagnosis and classification, speaker identification, picture analysis, interpretation, and more in response to claims that their systems include disease diagnosis and classification, speaker identification, picture analysis, interpretation, and more. Neural networks, symbolic learning, and statistical approaches all emerged as electronic computers became more widely used in the 1950s and 1960s. Machine learning technologies enable learning by allowing systems to discover the answer by drawing on their prior experiences. A network must have input data to operate with in order to produce meaningful outputs. To effectively apply machine learning methods, which are then tuned to provide reliable predictions, a thorough understanding of training data is required. The fundamental motives of the models are data obtained during training and applied to new, unseen data with the purpose of making accurate predictions. The more modern machine learning systems are classified as supervised learning. Computer-assisted information retrieval, or CAIR, is the process of using computers to discover and gather information. The numerous input-output examples aid the software in performing a wide range of specific data processing activities. Complications with medical imaging include skin blemishes, cardiac risk factors, and brain malignancies. While the simplest and most crucial objective of machine learning is to make data learn automatically to build challenging patterns, the machine learning system should then make smart decisions based on that data. Machines that have been around for a while are classified into a variety of categories based on their field of application. Machine learning is one of the most commonly used tools in this industry. This graphic, which depicts the relationship between various detection, segmentation, classification, and recognition approaches, is frequently used to distinguish between useful and currently used techniques.

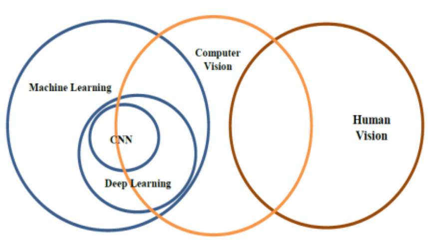


Fig.1 machine learning, deep learning, CNN, human vision, and computer vision

Deep learning has developed as a novel and inventive approach to dealing with the complexities of unstructured, loud, and massive data. Despite the fact that deep neural networks are not universal function approximators, they are referred to as such. With this increased computational power and memory, the researcher can create deep neural networks with a myriad of layers[1]. DNN is built on imitating the structure of neuron layers. Deep learning has three major advantages: Transfer that is simple, scalable, and less complex [2].

Manually produced features are derived from either raw data or models that are based on another key machine learning principle. Computers develop unique approaches to and characterize raw data by analyzing it, hence decreasing the need for manual labor. The two most common forms of deep learning models are ANN (artificial neural network) versions. Feature learning is one of the most well-known benefits of deep learning systems. The adoption of deep learning algorithms is another key difference in medical imaging [3].

II. REVIEW OF LITERATURE

A.Segmentation and Image Processing

Image pre-processing is a critical first step that involves computer analysis of skin lesion pictures. Applying post-processing processes ahead of time is critical since it is necessary to first specify the required dataset of an image because the approach employed will differ depending on the application. Pretreatment approaches are critical for image enhancement and restoration [4,5]. To reduce image noise, the researcher uses a Gaussian smoothing process called Gaussian smoothing [6]. In this effort, the researcher applied 3x3 Gaussian smoothing filters to the image. This is due to the fact that in 2D convolution processes, the researcher applies Gaussian smoothing filters to "blur" images and remove hair and noise.

Skin problem classification, which is based on images that focus on patients' subjective perceptions of sickness features, is critical for obtaining a correct diagnosis. Skin disorders are classified into two types: those that affect the skin's surface and those that enter the body. For starters, instead of using the traditional way for diagnosing skin ailments, a deep learning-based categorization strategy is detailed in greater detail here. [7]. As part of an integrated diagnostic method, a combined disease area segmentation and classification step could be employed [8]. Prior to extracting disease regions, skin lesion images must be filtered to remove background noise [9]. Disease segmentation and classification [10] can be accomplished using a method that does not rely on noisy pictures and is believed to have potential efficacy. The application of machine learning has overcome a drawback of the traditional skin diagnosis technique and computer vision of skin illness machine learning-based. A combination of machine learning and cutting-edge innovation is utilized in conjunction with cutting-edge technology to extract features and diagnose skin problems.

The machine learning technique for skin illness is beneficial in studying the various elements of skin diseases. Classifying skin disease features entails manually setting extractors and then using them to classify skin disease features. The application of machine learning methodologies necessitates a significant amount of effort predicting medical research in order to conduct substantial exploratory research to reduce the dimension of the data.

After the process is completed, the results can be received, which takes a long time and a lot of effort. Only in the same domain is feature engineering feasible. These constraints stymie machine learning advances in skin disease identification.

Deep learning for image recognition has yielded superior outcomes. Without the need for feature engineering, this bidirectional relationship can be derived automatically. The extraction efficiency is also good. The technology is adaptable and easy to alter. The primary application of deep learning in skin diagnostics is skin illness classification.

The classification assessment is now complete. Benign or malignant neoplasms cause over two-thirds of all skin issues. Benign skin tumors are a type of skin cancer that is fast growing and characterized by small lesions that might be difficult to detect. In research, benign neoplasms such as a simple wart [11] and seborrheic keratosis [12] are commonly used.

To get features from deep learning training, a large amount of training data is required. Collecting large-scale photographs of skin sickness, on the other hand, is difficult due to the unique qualities that must be preserved, such as the patient's privacy. Because of the ubiquity of skin disease presentations, the bulk of skin disease-related data in academia is labeled by specialists who are familiar with that skin disease presentation.

However, it is expected that in the future, the distribution of skin disease records will change away from self-collection or public sources and toward personal data. Self-collected datasets appear to be less easily accessible to the public due to their particular acquisition. The majority of published dermatological datasets include imaging data from dermoscopic imaging, dermoscopic image databases, and dermatological image databases [13–19].

III. METHODOGRAPHY

A.Proposed Methodologies

The researcher begins this section by offering an outline of our proposed methodology. Finally, four critical components are described in the following sections. The essential components of our proposed dermatological identification system are depicted in Fig 2 before the model is provisioned with skin photographs, which are pre-processed (e.g., cropped, resized, and augmented). VGG16, ResNet50, Xception, MobileNetV2, InceptionV3, and DenseNet121 were also used as deep learning training models. A set of MLclassifiers is used to analyze extracted features from previously trained DNN models. The top four deep features, known as "Inception V3," "Random Forest Classifier," "Gaussian Nave Bayes," and "Support Vector Machine," were chosen because they produced the best results among the classifiers. Within our ensemble module, the four most important deep features are concatenated, and those features are used as inputs to machine learning classifiers that use Voting to predict the final decision. The class for categorization issues is determined by a majority vote.

B. DETAILS ABOUT THE DATA SETS

There are several invasive skin imaging treatments available, such as dermoscopy, that make spots easier to view and differentiate. It is possible to maximise the effects of the deeper skin layer by reducing surface reflection. The network's training, validation, and testing the were aided by the usage of over a thousand ISIC Dermoscopic Archive images, all of which the were freely available to the public. The ISIC is a collaboration betweenacademia and industry aimed at bringing digital skin imaging to a wider audience. ISIC wants to develop digital skin imaging while also integrating dermatology and computer science. There are a total of 69445 photographs. Images with a file size more than 1MB.

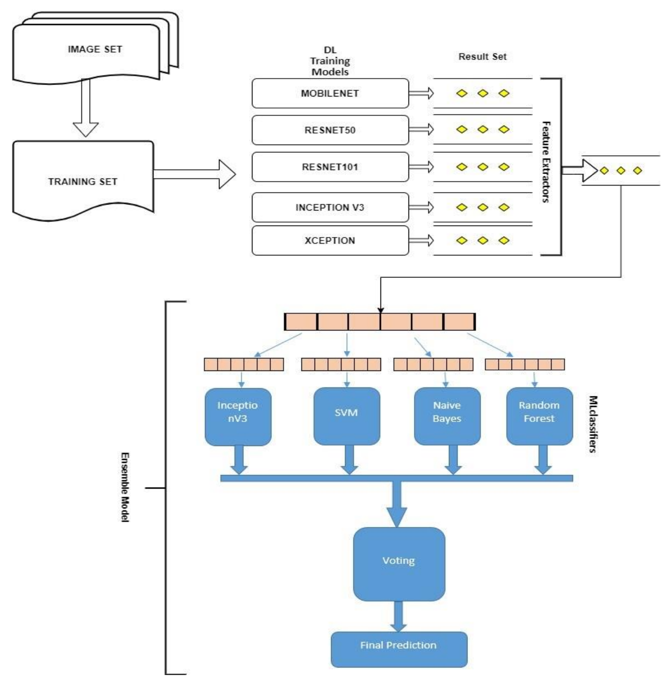


Fig 2. The architecture of our proposed method Skin Disease Ensemble Classification Using Transfer Learning and Voting Classifier

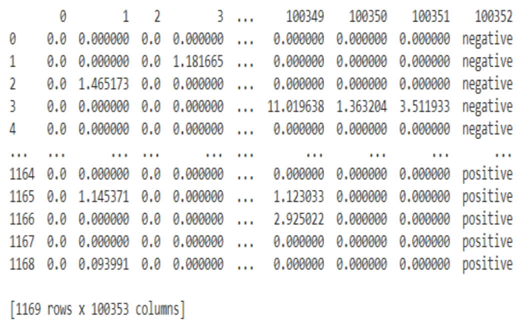
C. Pre-Processing

Before proceeding to the next level, the researcher must perform a series of basic tasks that will aid in the identification of skin disorders utilizing our images. The goal of this technique is to produce fundus photographs in a consistent and distinctive manner. The researcher achieved this by scaling photographs with the same radius and then removing the average color of the surrounding area. To remove any unnecessary details, 224224 pixels were cut out of the image around the segmented image.

Procedures for training and testing the model with unseen data are used in our experiment. The data were divided into three groups at random to generate the training, validation, and test sets. TABLE I displays the photos that were used for training and assessment. Figure 3 depicts the data model for the experiment results.

TABLE I. Images used for ongoing training

Training Set	Validate set	Test set
1169	695	474



	0	1	2	3	...	100349	100350	100351	100352
0	0.0	0.000000	0.0	0.000000	...	0.000000	0.000000	0.000000	negative
1	0.0	0.000000	0.0	1.181665	...	0.000000	0.000000	0.000000	negative
2	0.0	1.465173	0.0	0.000000	...	0.000000	0.000000	0.000000	negative
3	0.0	0.000000	0.0	0.000000	...	11.019638	1.363204	3.511933	negative
4	0.0	0.000000	0.0	0.000000	...	0.000000	0.000000	0.000000	negative
...	...	...	...	...	...	...	...	...	...
1164	0.0	0.000000	0.0	0.000000	...	0.000000	0.000000	0.000000	positive
1165	0.0	1.145371	0.0	0.000000	...	1.123033	0.000000	0.000000	positive
1166	0.0	0.000000	0.0	0.000000	...	2.925022	0.000000	0.000000	positive
1167	0.0	0.000000	0.0	0.000000	...	0.000000	0.000000	0.000000	positive
1168	0.0	0.093991	0.0	0.000000	...	0.000000	0.000000	0.000000	positive

[1169 rows x 100353 columns]

Fig 3. Data Set Model

D. Feature extraction using pre-trained models

a) Transfer Learning

In the realm of deep learning, the two essential types of transfer learning are feature extraction and fine-tuning. To train a feature extractor, utilize a traditional dataset such as ISIC but remove the top layer for classification. Following model pretraining, a separate classifier is trained to perform classification. To extract more features from the dataset, an arbitrary feature extractor is utilized. Fine-tuning involves adding the weights to a previously trained model, which are subsequently utilized as the starting values in training. During the fine-tuning operation, the weights used in training are adjusted and renewed. While these weights are sufficient as generic feature maps, they should be fine-tuned for the new dataset to account for its unique properties. When it comes to fine-tuning, it's all about changing general characteristics to meet a specific goal. The training data was utilized for training the weights that would be used in the transfer learning approach, which were then used to compensate for the lack of training data. Transfer learning was employed to keep the models from overfitting due to the limited dataset. Deep learning algorithms applied to images of skin diseases can help to automate the diagnosis process and serve as a useful tool. Six deep-learning training models were used to extract the features: VGG16, ResNet50, Xception, MobileNetV2, InceptionV3, and DenseNet121.

b) Feature Selection

The factors in the data used to train a machine learning model have a major impact on its efficacy. Model performance may be hampered by features that are irrelevant or only partially relevant. The researcher created feature selection methods based on machine learning techniques for analyzing machine learning data using Python's scikit-learn package. Feature selection is a machine learning technique used to choose only the most important components of our skin data. As a result of irrelevant data features, overall accuracy was compromised. The researcher was able to achieve a number of advantages by employing this method, including

There is less redundancy: Reduces the amount of redundant data, which means less potential for wrong conclusions due to data noise. More accurate modeling will come from less misleading data. Training algorithms can accomplish more jobs in less time because there are less data to process. If the importance of the feature values falls below a certain threshold, the features are deemed ineffective and are removed. The entire outcome, as indicated in TABLE II, is what the researcher has.

TABLE II. Investigated Performance Model

Model	accuracy(acc)	F1-score	precision	recall
Mobilenet	0.9012	0.9017	0.9038	0.8998
inceptionV3	0.9023	0.9038	0.9054	0.9022
ResNet-50	0.9298	0.9293	0.9298	0.9288
Xception	0.9336	0.9345	0.9367	0.9324
ResNet-101	0.9469	0.9354	0.9359	0.9348

c) Classification

It incorporates a machine learning technique in the prediction process, which integrates a number of diverse models. The most widely used models in research are biased estimators. This technique can handle the following technical issues in the construction of a single estimator:

a model with a high level of variability: The learned qualities are highly dependent on the given inputs.

Precision is low: Fitting the entire training dataset with a single model or approach may be insufficient.

Because it relies on a small number of features to produce a prediction, the model has some bias and noise.

d) Ensemble Algorithm

Using a single algorithm on a given dataset does not result in the best forecast. Although machine learning systems contain flaws, constructing reliable models is tough. The researcher may be able to improve overall accuracy by combining several models. An organization can reduce overall model error while maintaining generality by integrating model outputs.

A voting ensemble is a machine learning model that aggregates the predictions of various machine learning classifiers. When compared to individual models, ensemble processing usually produces greater overall model performance, especially when ensemble approaches are used. To make a final conclusion, the voting ensemble examines forecasts from multiple models. The researcher model the forecasts for each label by aggregating the individual projections and selecting the label with the highest number of votes.

This suggested ensemble soft voting classifier uses majority voting to merge several machine learning models aiming at the same or different goals, concepts, or subjects. Voters are divided into two groups based on the voting criterion: hard and soft. Finally, the aggregator will choose the class prediction that appears in the core models the most. Soft voting requires the incorporation of Predicting into the foundation models. The voting classifier achieves improved overall results by incorporating several research models into the classifications. The recommended model employs Logistic Regression, Naive Bayes, Random Forest, and SVM. The predict characteristic column of the soft voting classifier was used to develop a voting classifier that leverages the probability allocated to each target variable. The training data is mixed in this scenario before being put into one of four machine learning models: logistic regression, Nave Bayes, Random Forest, or SVM. In this model, individual predictions are processed using the aggregator voting method in conjunction with the soft voting methodology. The final prediction is then made using the majority vote technique.

IV. IMPLEMENTATION AND RESULTS

A. Tools TensorFlow

The researcher used Keras Deep Learning Library with the Tensor flow as backend. All experiments related to this study were conducted on Colab or Google. Keras offers image analysis models that have been pre-trained.

Colaboratory: - a product from Google Research that provides free GPU service for education and research purposes. The GPUs obtainable in Colab often include T4s, Nvidia K80s, P4s and P100s

B. Model summary

Color photos will be 224 by 224 pixels in size, according to this model. The first step is to load and reorganize the photo such that it is a 224X224 square, as specified by the model, and then scale the image pixels accordingly. Because the model works with an array of samples, when importing a picture with 224X224 pixels and three channels, the size of the imported image must be increased by one.

To achieve better outcomes, the researcher fine-tuned our model's hyperparameters. A multidimensional tensor can be serialized progressively using the Flatten formula (typically the input one). This option provides a transformation between the input tensor and the first hidden layer. Because the hidden layer(dense) was trained for 25 epochs with varied batch sizes, each item of the (serialized) input tensor is linked to one of the hidden array's elements (Shown in Fig 4). Batch dimensions have a substantial impact on the model's capacity to replicate learning patterns appropriately.

The accuracy of 94.6 percent is astounding.

```
[0 0 0 ... 1 1 1]
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 10000)             88620000
_________________________________________________________________
dense_1 (Dense)              (None, 5000)              50005000
_________________________________________________________________
dense_2 (Dense)              (None, 2000)              10002000
_________________________________________________________________
dense_3 (Dense)              (None, 500)               1000500
_________________________________________________________________
dense_4 (Dense)              (None, 300)               150300
_________________________________________________________________
dense_5 (Dense)              (None, 200)               60200
_________________________________________________________________
dense_6 (Dense)              (None, 120)               24120
_________________________________________________________________
dense_7 (Dense)              (None, 30)                3630
_________________________________________________________________
dense_8 (Dense)              (None, 30)                930
_________________________________________________________________
dense_9 (Dense)              (None, 1)                 31
=================================================================
Total params: 149,866,711
Trainable params: 149,866,711
Non-trainable params: 0
_________________________________________________________________
```

Fig 4. Model Architecture

C. Hyperparameters

The hyperparameters of machine learning models are their settings. These are the parameters or variables that allow the model to be customized for a particular project or dataset. The optimizer for transfer learning was ADAM, the loss function was binary cross-entropy, and a having to learn the rate of 0.001 with a batch size of 4 was used, as shown in Fig 5.

Hyper Parameters

Parameter	Values
Optimizer	Adam
Loss Function	Binary Cross Entropy
Learning Rate	0.001
Epochs	25
Batch Size	4

Fig 5. Hyperparameters

D. Results

Four machine learning models are used in the suggested methodology. The first is called Random Forest. The second method is known as Logistic Regression. The fourth is known as SVM, and the third is known as Nave Bayes. An experimental technique was used to investigate the ISIC Skin dataset. The dataset contains 769 data points and 10 feature columns, with 769 data points having their medians replaced by zero median values. The training area is utilized for the training sample 80% of the time, while the testing section is used for the testing dataset 20% of the time. When it comes to algorithm analysis, the most generally utilized assessment metrics are accuracy, precision, and F1 score. A true positive occurrence occurs when both the predicted and actual class values of "positive" are 1. True negative (tn) means that the predicted class has a value of 0, and so does the actual class. False negatives (FN) and false positives (FP) are errors that occur when the expected and actual classes vary (FP). The most important metric is accuracy, which is defined as the ratio of properly predicted to total observed observations. This was done in order to determine and compare the accuracies of all standard algorithms. The skin dataset was divided into two categories: positive and negative. The graph below summarises the outcomes of the machine learning models in Table 2. With an accuracy rating of 0.9558 (Table III), the ensemble soft voting classifier is the most accurate machine learning technique. These figures show that the accuracy of each of these approaches is 0.9218, 0.9324, 0.9065, and 0.9246. In Table III and Figure 6, all methods have been thoroughly explored.

TABLE III. FINAL PRDEICTION

Classifier	Accuracy
Logistic Regression	0.9218
Random Forest Classifier	0.9324
Gaussian Naive Bayes	0.9065
Support Vector Machine	0.9246
Ensemble	0.9558

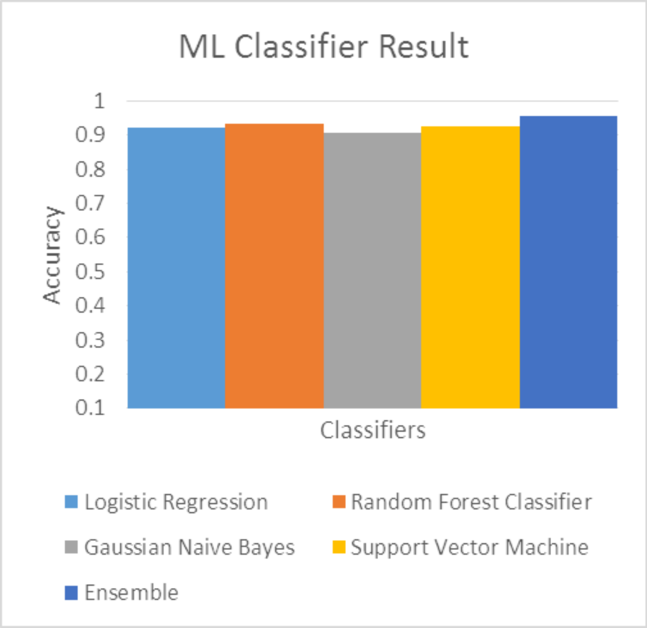


Fig 6. ML Classifier

Fig 7 displays ROC curves, where the Receiver Operating Characteristic (ROC) is shown on the y-axis, and the FPR is shown on the x-axis, regardless of the threshold. The ROC curve data shown in Table III are used in this manner. When evaluating ROC curves for skin disease datasets, the suggested model's ensemble model coverage percentage is found to be 95.5 percent. As indicated in Table III, other base classifiers have less than Ensemble.

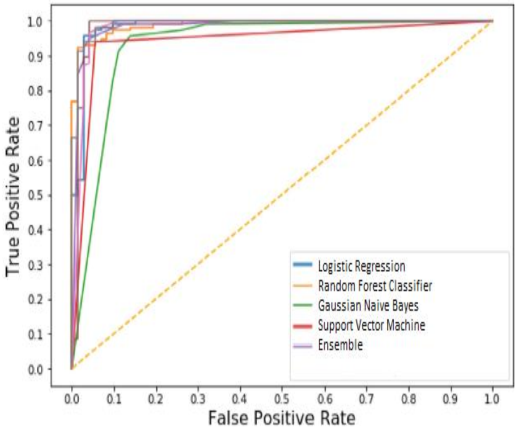


Fig 7. ROC Curve

With an accuracy of 95.5 percent, Fig 8 illustrates our classifier's ability to categorize correctly or erroneously predicted images of skin data set photos.

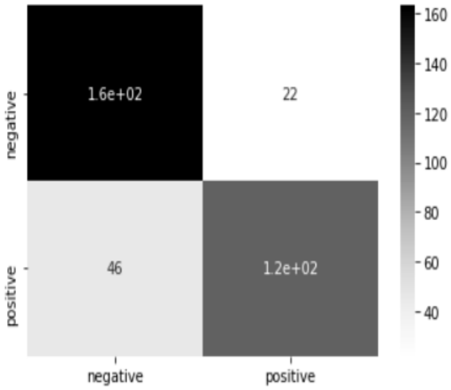


Fig 8 . Confusion Matrix for Ensemble Model

V. CONCLUSION

Transfer Learning is utilized in conjunction with an ensemble of ML classifiers, including a voting classifier, to categorize skin diseases. In order to obtain vital information, the researcher used a huge number of pretrained DNN using skin ailment photographs. Multiple ML classifiers are then used to analyze the obtained deep features, with ResNet 101 having the highest accuracy of 0.94. To appropriately categorize test data, a machine learning model combines multiple deep features linked together as an ensemble of deep features. After that, the model is passed into a voting classifier, which predictions the outcome. To categorize skin illnesses, the researcher used a number of pretrained DNN and ML classifiers, as well as the 5 separate pretrained DNN. The results suggest that the ResNet 101 deep features structure is an excellent fit for datasets with a substantial amount of data and two classes. Furthermore, for datasets with a large amount of data and multiple classes, an ensemble of ML Classifier deep features is an excellent choice for a classifier. Furthermore, the majority of skin disease classification tasks beat other ML classifiers. Finally, here is a summary of our innovative feature ensemble method: This method helps to overcome the limits of a single CNN model, which is especially useful when working with huge datasets. Each label's projections are pooled, and the label with the most votes is forecasted using the approach the researcher suggested. Our proposed method's accuracy is promising, but more study is needed to be done with a larger model size so that it may be used on a real-time medical diagnosis system.

APPENDIX A

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