A Deep Multiclass Learning Approach for Analysing Human Skin Lesions Using Ensemble Regional Dense Neural Networks (ERDNNs)

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ABSTRACT

Melanoma is considered to be one of the deadliest skin cancer types, which is found among 5% of western countries population. The lack of awareness and few practical difficulties in identification of the disease are the main factors in increasing the mortality rate due to skin cancer. The treatment given for this particular type of cancer remains problematic, because of its pigmentation resemblances with normal skin lesions. The clinical examinations of the Melanoma are mostly happening after the second stage of the lesions, which remains a huge problem in giving perfect treatment to the skin cancer within short duration. The Deep learning researchers remunerated more attention in implementing the procedure of Melanoma identification in computer vision-based approach to solve the inefficiency of manual inspection. The classification and prediction stages in Deep Learning are more accurate and time restraint factors for decreasing the mortality rate due to Melanoma. The research work carried out in gives more attention in giving the best rule setup in digital image processing as well as in deep learning procedure. The proposed Ensemble Regional Dense Neural Network (ERDNN) eradicates many issues faced previously during manual inspections and segments the affected parts accurately. The initial stage of the framework follows the basic digital image processing stages for picking the colour channels and enhancing the quality of the collected images from HAM10000 and HAM datasets. The feature, wrapper and embedded based feature selection process is carried out with convolutional method as well as with Deep Neural Network CReLu for Segmentation procedure. The furthermost procedure of the research is to examine the segmented images with proposed ERDNN for identifying the severity level of Melanoma. The comprehensive measurement is carried out with confusion metrices for testing the accuracy of the proposed ERDNN with other existing classification models. The performance of the ERDNN in concern to accuracy is 95% which is far better than other existing models.

Keywords: Conventional method, Pooling. Basal cell carcinoma (BCC), Squamous cell carcinoma (SCC), Melanoma

1. Introduction to Deep Multiclass Learning Approach

Over the past ten years, there has been an increase in the development of skin cancer [1]. Sunlight's ultraviolet radiation induce long-term skin damage and the development of cancer cells [2]. These kinds of circumstances typically include unstated dangers that increase the chance of skin cancer as well as psychological discomfort and a lack of confidence in people. There are various forms of skin cancer such as squamous cell carcinoma, actinic keratosis, melanoma, and basal cells [3]. Actinic keratosis, sometimes known as solar keratosis, is compared with squamous cell carcinoma [4]. Both melanoma and nonmelanoma incidence rates are rising annually [2]. Melanoma is the deadliest type of skin cancer, and because melanocyte neural crest neoplasia is malignant, it spreads swiftly to other body sites [5]. The process used in healthcare to identify skin cancer discovers the disease's presence only after numerous diagnostic tests and clinical trials, many of which are insufficient to provide a patient with an appropriate course of therapy. There aren't many issues with the skin cancer treatment procedures that allow for accurate and timely results. The patient has basal cell skin cancer if the cancer starts in the skin's basal cells. When the skin's pigment-producing cells become cancerous, melanoma results. Melanoma skin cells are among the skin conditions that have a notable fatality rate. Melanoma survival rates rise significantly if it is discovered in its very early stages.

Skin cancer melanoma is far more difficult to identify and can cause harm to the liver, bones, lungs, and brain if it is not found in its early stages. Clinical photography is commonly utilized for the initial clinical examination of melanoma. A noninvasive method of image analysis called dermoscopy is widely used to assess melanoma lesions. In situations of skin cancer, dermoscopy is utilized to determine the patterns of melanoma lesions. Additionally, this Dermoscopy technique can be used to identify the vascular components of skin lesions. The instrument utilized to diagnose the vascular components is the dermoscopy, a general microscope with notable lens quality and a magnifying quality of more than ten times.

In order to analyse skin illnesses, data mining technologywhich has advanced quickly in recent years—is crucial. Academics are always coming up with new prediction approaches, but most of them are ensemble methods based on a limited set of categorization algorithms. The ensemble method combines a number of data mining techniques to find predictions. Machine learning techniques combined with computer vision mission-based approaches are well-known technologies to address numerous problems in the identification process used in the illness prediction process. The following fundamental image processing techniques can be used to carry out the object identification in the images.The following fundamental image processing techniques can be used to carry out the object identification in the images. The work being done in the area of computer vision-based approaches is particularly helpful in separating the afflicted from the healthy sections. Most people believe that melanoma infections are uncommon, albeit they have the potential to progress to malignancy at some point. Doctors find it extremely challenging to distinguish melanoma infections from other skin infections because of their striking similarities to other skin illnesses that affect humans. Early in 1987, the melanoma diagnostic process was started, although many identification procedures fail to provide a suitable solution at an early stage.

Early-stage forecasts could assist dermatologists in providing an appropriate treatment for the issue at hand in the shortest amount of time. This specific section of the research work explains the feature extraction and pre-processing method used to detect the areas of human skin affected by melanoma. A few cleaning procedures and a feature selection process are used in this study work's procedure, which ultimately concentrates the research's findings. The gathered dataset is cleaned, or the irrelevant images are removed, before being used for filtering processes, which involve image improvement. Choosing the features required for the prediction stages is the last step in the pre-processing process.Feature selection is an essential stage in the processing of skin lesion images; it finds the most significant and informative characteristics to help with the precise identification and categorization of skin lesions. Feature selection reduces data complexity, increases algorithm processing efficiency, and improves the performance of skin lesion diagnosis models.

Images of skin lesions often capture a variety of characteristics, such as shape, texture, colour, and spatial information. However, not all traits are equally valuable or considerably helpful in identifying skin lesions. Feature selection enhances the accuracy and efficacy of identification models by removing unnecessary or redundant data and assisting in the identification of the most significant and discriminative attributes.The analyzing the melanoma and giving the necessary treatment are the final stage of this research work, which is carried out with deep learning approach. The procedure followed in the deep learning are most unique way of representing the affected area of the skin from unaffected part of the skin. Dense neural networking approach for segmentation are the most significantly used approach in classification of the skin lesions. Machine learning and deep learning plays a pivotal role in segmenting the severity of the melanoma infections.

2. LITERATURE REVIEW

Numerous scholars have suggested that image processing be used to detect cancer and other skin conditions. Some of the strategies included in this section's material can be skipped by the researcher. Color pictures from [2] can be used to detect skin conditions that can be self-treated without a doctor's help; [3] explains this method. In the first stage of the classification process, color image processing techniques, k-means clustering, and color gradient algorithms are used to detect skin disorders; in the second stage, artificial neural networks are used to categorize different types of diseases. Six distinct skin conditions were used to evaluate the approach, and the standard accuracy in the first stage was 95.99%, and in the second stage, 94.016%.

The process becomes increasingly accurate the more properties that are extracted from a picture using this technique. Up to 90% of the operations performed by the researcher in [3] to treat nine different skin conditions were effective. If melanoma is not properly diagnosed and treated in its early stages, it may be fatal [4]. The researcher investigated several segmentation methods that might be applied to image processing in order to detect melanoma, and he made the decision to reveal his findings. A thorough description of the process of segmenting along the sick patch's borders is given to extract more characteristics. suggested creating a melanoma diagnostic tool that individuals with dark skin may use to check if they had the condition.

Consequently, [1] presented a computer system that was able to identify eczema and determine its severity on its own [6]. In order to identify and correctly segment skin, three stages must be taken: first, a collection of characteristics, such as color, must be retrieved; second, Support Vector Machines (SVM) are used to assess the severity of eczema; and third, SVMs are used to assess the severity of eczema. [6] outlines a cutting-edge method that makes use of computer vision and machine learning capabilities to diagnose skin problems. Not only is machine learning used to diagnose skin conditions, but it is also utilized in computer vision to get data from images. Deep CNNs have gained traction recently for use in image classification and feature learning, among other uses. Extensive ImageNet studies show that traditional deep CNN-based object classification techniques outperform human object classification skills. Large amounts of data can be used to train a network in order to achieve the necessary results and efficient GPU performance.

A computerized approach for lesion identification and localization was provided by Afshar et al. [8]. They employed RCNN architecture to obtain deep features for lesion localization. Next, Newton-Raphson (IcNR) and artificial bee colony (ABC) optimization are used to choose the optimal characteristics. A hybrid method was created by Daghrir et al. [5] to identify suspicious lesions that might be examined for melanoma skin cancer. They employed two classical classifiers and a coevolutionary neural network in three distinct techniques. The suggested algorithm was simpler to use, more realistic, and more reliable. Using the HAM10000 dataset, the experimental approach achieved an accuracy of 85.8%. Additionally, an evaluation of our technique using the five-class KCGMH dataset revealed an accuracy of 89.5%. An automated electronic device was shown by Kumar et al. [9]. A number of parameters were taken into account, including skin colour, asymmetry in the skin, damage caused by skin cancer, and the form of the afflicted region. To separate homogenous image areas, they employed fuzzy C-means. First, certain texture characteristics are extracted, and then the Differential Evolution (DE) method is trained. -A HAM10000 accuracy rate of 97.4% was obtained via the experimentation method.

A classification paradigm based on geometric and textural data was put out by Shayini [2]. ANN was utilized for the final feature categorization. Tajbakhsh et al.'s [7] demonstration of the superiority of utilizing a pre-trained network over creating a deep CNN from scratch also supports this claim. Even in the case of unmarked input data, this remains true. Scientists were able to solve the issue without creating a deep CNN from scratch by using a trained network on images with some past knowledge of medical events. Giotis et al. developed an extensive technique that utilizes CNN deep networks and takes into consideration a wide range of characteristics, such as lesion texture, size, color, and so on. Hassle developed a method that uses deep neural networks to classify binary diagnoses from dermoscopic pictures. These categories can then be used to diagnose a patient. A deep CNN-based ECOC SVM was employed by Dorj et al. to categorize skin cancer photos into four "diagnostic categories." A deep CNN-based image classification technique was reported by Han et al. in a Science publication. This method was utilized to classify images obtained during clinical trials of around twelve distinct types of skin diseases. Authors Mohd and colleagues suggested segmenting pictures for this melanoma investigation rather than use a detection method. The dataset used for this investigation comprised four distinct skin conditions.

They established the strategy's success in a comparable case. German et al. employed AdaBoost MC in a follow-up investigation to corroborate the early skin cancer detection approach. Jaffar and Almansour developed the technique for categorizing melanoma. They arrived at these results using fuzzy, Support Vector Machine (SVM), and k-means clustering algorithms. The information from individual skin lesions is coupled with additional criteria to diagnose skin cancer. Ioannis and colleagues developed a system that may use a wide range of data, including visual diagnostic structures with unique characteristics for the damaged zone of lesion texture, color, size, and placement within the damage %. They accomplished this by combining fully convolutional neural networks with image processing algorithms.

3. PROPOSED METHODOLOGY

The stages followed during the analysing stage completely follows the deep learning and neural network procedure. The collected information is pre-processed in the earlier stage using digital image processing and necessary features are identified for the final Melanoma severity identification procedure. The filtering technique followed in the feature selection process is most useful in enhancing the quality of the collected images. The final stage of the research work is to segment the processed images with deep learning algorithm. The proposed Ensemble Regional Dense Neural Network (ERDNN) is used for the classifying and analysing the collected Melanoma images. The procedure followed in the proposed framework is given in Fig 1.

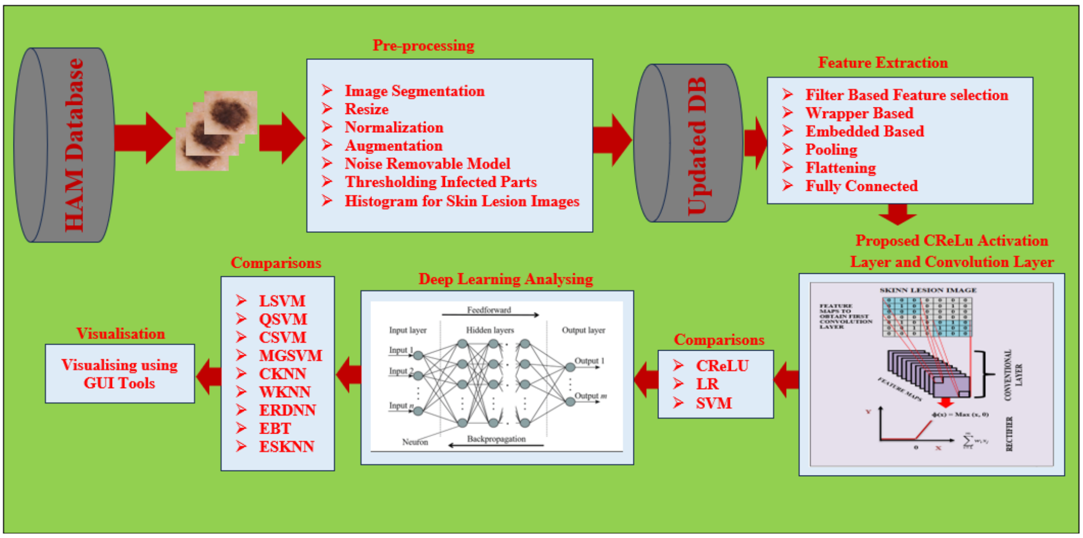

Figure 1. Architecture of proposed ERDNN model

The complete overview of the proposed ERDNN model is shown in the fig 1, which starts with the data collection stage. The goal of the research is to categorize the existence of melanoma in the dataset and determine the type of skin lesions that are present on the gathered images. The cells that were recognized from the gathered images as malignant and beginnings are thought to be the cancer's origins. The first step of the research involved transforming the gathered images into formats that would function well for simulations. The test histograms for RGB, HSV, LCH, and LAB show the colour distributions over the affected areas of the skin lesion. The graph's highest point represents the color's high intensity range. These gathered histogram peaks are used to test the different kinds of skin lesions. Variations in mild, moderate, and severe skin-infected disorders are also considered in this method.The initial steps in the research process are regarded as the preparation of digital image processing. This specific study article describes the feature extraction process used to choose the attributes required to detect the presence of melanoma in skin lesions. The acquired outcomes are used in the analysis phase. Convolution Rectifier liner unit (CReLu) is a hybrid machine learning technique designed to identify skin lesions. In order to simulate the outcomes, this proposed CReLu essentially employs a deep neural networking technique for user InterVision. The ultimate stage followed in the research work is to analysis the segmented images with deep learning methodology. The proposed ERDNN algorithm is used as the classifier for the segmenting the melanoma infections based on the severity levels.

3.1. Database description

A dataset of images depicting six prevalent skin diseases on the face was the main result of this endeavor. The Human Against Machine with 10,000 training images (HAM10000 dataset), available on Kaggle, was used to construct the images in the dataset. At least three extremely skilled dermatologists thoroughly examined these images and labels. The public will be able to access it after all necessary procedures are completed. The collected images have irrelevant images and duplicates images, which may affect the complete flow of the research work.

3.2. Pre-processing the collected melanoma images

A model's capacity for generalization can be enhanced by high image quality. Preprocessing can increase dependability, streamline the data, reduce superfluous information in an image, and increase the intensity of important information. Image processing is necessary to accurately examine skin lesions. Image processing helps in the identification of affected areas on human skin. The images collected from various medical datasets are stored in central systems, and all analysis is done using image processing techniques. Preprocessing is essential for jobs involving the detection of skin lesions because it improves the quality of the input data and retrieves pertinent information. Skin lesion images may vary in size, thus it's critical to adjust them to a uniform size.This guarantees that the model processes each photo in an identical manner. Re scaling contributes to lowering the computing cost of succeeding phases as well.

Colour shifts in skin lesion images can be caused by several factors such as camera settings, illumination, and image collecting characteristics. By using colour normalization techniques like colour constancy algorithms and histogram equalization, the colour distribution across numerous pictures can be made uniform. Image noise may cause lesion identification algorithms to perform less well. Important features can be preserved during noise reduction by using methods like median filtering and Gaussian blurring. Improving the contrast and sharpness of skin lesion images may help draw attention to key aspects. Image-enhancing techniques including gamma correction, histogram stretching, and adaptive histogram equalization can be used.

Skin lesion segmentation, which attempts to separate the lesion site from the surrounding healthy skin, is a crucial stage in the procedure. To extract the lesion area, a variety of segmentation techniques are available, such as thresholding, region-growing, and active contour models. Data augmentation strategies can be used to improve the model's ability to generalize by increasing the variety of the training data. To generate additional training cases, these techniques apply random zooms, flips, translations, and rotations. After preprocessing, key features from pictures of skin lesions must be retrieved. It could be essential to apply convolutional neural networks (CNNs), which are trained deep learning models, for techniques like texture analysis, shape analysis, and feature extraction. Image segmentation, resizing, argumentation, noise removal, normalization, threshold infected part and histogram are the techniques followed in the pre-processing stage. Before taking the final preprocessed images into the feature selection process, images are carefully stored and maintained in the additional database.

3.3. Feature selection procedure

The feature selection process and extraction process play a major role in filling the accuracy gap of the research work. One function that may be found in the Azure Machine Learning designer is Filter Based function Selection. This part aids in locating the input dataset's most predictively powerful columns. In general, feature selection is the process of using statistical tests on inputs to determine an output. The objective is to identify the columns that are more representative of the result. Numerous feature selection techniques are available through the filter-based feature selection component. The component uses chi-squared computations and Pearson correlation as correlation techniques. The dataset is supplied, and it is indicated which column in the Filter Based Feature Selection component contains the dependent variable or label. The next step is designating a single technique for calculating feature importance.

Based on predictive power, the component generates a dataset with the best feature columns. Additionally, the feature names and corresponding scores determined by the chosen measure are output. Since the chosen metric is used to identify unnecessary attributes, this stage of feature selection is known as "filter-based" feature selection. After that, you utilise a filter to remove any unnecessary columns from your model. A score is assigned to each feature column by the component based on the one statistical measure that most closely matches the processed pixel. The columns are given back in the order of the feature scores.

Feature selection metric: Numerous metrics are available in the Filter-Based Feature Selection component to evaluate the importance of the data in each column. A brief description of each measure and the circumstance in which it is used is given in this section. The technical notes and configuration guidelines for each component contain additional criteria for using each statistic.

Pearson correlation: Pearson's correlation statistic, often known as Pearson's correlation coefficient in statistical models, is also known by the term "r value." It produces a result that indicates the degree of correlation for any two variables. By dividing the covariance of two variables by the product of their standard deviations, one can calculate the Pearson's correlation coefficient. The coefficient is unaffected by changes in the respective scales of the two variables.

Chi squared:A statistical technique that evaluates how closely expected values match actual outcomes is the two-way chi-squared test. For every variable, the methodology presupposes that a sufficient sample of independent variables is chosen at random. The calculated chi-squared value shows how much the real findings differ from the predicted (random) outcome.

Wrapper-based feature selection: The feature selection procedure in wrapper approaches is predicated on a particular machine learning algorithm that we attempt to fit to a given dataset. It compares each and every feature combination to the evaluation criterion using a greedy search methodology. One assessment criterion that varies according to the type of issue is the performance metre. It is possible to derive the criteria for classification assessment and regression, respectively, using f1-score, R-squared, Adjusted R-squared, and P-values, among other metrics. Ultimately, it chooses the mix of features that produces the best outcomes for that specific machine learning method.

Embedded-based feature selection: The advantages of filter and wrapper techniques are combined in embedded methods. It is implemented by algorithms that use integrated feature selection techniques.

Regressions with integrated penalization algorithms to reduce overfitting, such as LASSO and RIDGE, are among the most well-known instances of these methods.

Pooling: Following layer convocation, which modifies the layer mapping, was the pooling process. To improve feature processing accuracy and save processing time, the created layers are put into another pooling procedure. The pooling method may provide a clear image of the object and facilitate identification when determining the cause of a skin ailment. The two primary elements of the pooling technique are the maximum pooling value derived from continuous pooling operations and the average fixed pixel value of the skin lesion images. Maximum pooling in convolution neural networks is mostly used for sickness diagnosis. By applying the polling technique, the mapped features may be made less dimensional and the learning parameters can be decreased.

CNN processing employs two different pooling algorithms: average pooling and global pooling. The averages pooling filtering processes identify the average elements' presence in the region mapped following convolution stacking. The average pooling approach is typically used to find the average of the components in designated regions following the max-pooling process. Global pooling is the process of combining all channels into one and performing a single value conversion. To make the simulation process easier, three-dimensional channels like nh x nw x nc are reduced to a 1 x 1 x nc feature mapping. The approach is regarded as a feature mapping substitution in the nh x nw dimensions.

Flattening: The convolution layer and earlier pooling techniques are very helpful in obtaining the required characteristics since they use high-accuracy mapping. For a simple evaluation method used in the real neural network installation procedure, the feature mapping gathered during the pooling phase should be organized in column vice. The outcomes of the pooling process are likewise flattened using this technique.

Full Connection:A feed-forward neural network process that decodes the resulting mapped layers can be thought of as a fully linked layer. To create the neurons of the next layer, the active neurons will be connected via linear rectifiers. Before employing the dimensions of each layer in a fully integrated layering process, the dimensions must be converted into single dimension data. In order to convert the region created by the convolution layering and pooling technique into a one-dimensional format and get the required result for skin infection prediction, neural networking is used.

Proposed CReLu Activation layer and Convolution Layer: Various component layers are modelled by convolutional neural networks. The convolution layer applies is a crucial component of the CNN workflow. To improve the results, the convolution layer continually different processes to the acquired output functions. The procedure of feature mapping from the pictures of the skin lesions is carried out using convolutional techniques. The primary method of convolution layering involves identifying characteristics from input pictures of skin lesions. The photos of the skin lesions can be converted into spatial information on the data by using this layering technique. When choosing convolution kernels to train while taking CNN input into account, the layering's weighting is quite helpful.

Convolution layer mapping is followed by activating the required properties extracted from the mapping. A number of researchers use various activation strategies to filter the ordered layers. The Rectified Linear Unit is one of the filtering strategies used in current research to reduce or narrow down the convolution layers in order to precisely identify the areas affected by skin lesions. Rectified Linear Units can save training times and improve the precision of the Skin Lesion disease detection procedure when used in 3 X 3 convolution layers.Deep learning neural networks are trained using these unique activation functions, which perform well with unsupervised pre-processed input under non-linearity. The sigmoid function is frequently employed as an activation function in research projects, as opposed to corrected liner units. Convolution mapping layers use rectified liner units to provide very realistic simulations with little computational overhead. The corrected linear unit that was used to map the diseased areas of the Skin Lesion can also be applied to other complicated datasets for expedited computation and time savings.

The simplest activation function, where no transform is applied at all, is referred to as "linear activation". While all-linear activation function networks are relatively quick to train, they are not able to learn intricate mapping functions. The output layer of regression problems and other networks that forecast a quantity still employ linear activation functions. It is preferable to utilize non-linear activation functions since they enable the nodes to understand more intricate data structures. The hyperbolic tangent activation function and the sigmoid activation function are two common nonlinear activation functions.

Rectified Linear Unit (CReLu): The suggested convolutional approach with Rectified Linear Unit (CReLu) performance is determined using machine learning and deep learning techniques. The accuracy of the suggested convolutional algorithms is evaluated using a variety of machine learning techniques. This research project adheres to the liner method of representation in its methodology. Therefore, the comparison is done using the Liner representation techniques. The suggested CReLu method is used to assess the logical regression (LR) and support vector machine (SVM) approaches for predicting melanoma skin lesions from different lesions.

Logical Regression (LR): Logistic regression is a statistical method for determining the probability of an event occurring. It might be applied to determine an individual's probability of getting melanoma based on traits or risk factors. Either 0 indicates that the person has no melanoma, or 1 indicates that they have melanoma. The traits or variables could be things like age, sun exposure, and family history. The logistic regression model determines the probability that a particular set of features would result in the desired outcome, which is the existence of melanoma. Since each real number can be mapped into the interval between 0 and 1, the logistic function, also known as the sigmoid function, is appropriate for probability estimation.

$$P(Y=1)=\frac{1}{1+e^{-(b_0+b_1X_1+b_2X_2+\cdots+b_nX_n)}} \quad (1)$$

$P(Y=1)$ *is the probability of having Melanoma,*
$b_0, b_1, \ldots, b_n$ *are the coefficients*
$X_1, X_2, \ldots, X_n$ *are the features*

The logistic regression model is trained on a dataset containing known outcomes, and then its coefficients are adjusted to optimise the likelihood of the observed outcomes. It's a useful and understandable strategy for binary classification problems, like disease prediction.

Support Vector Machines (SVM): Support Vector Machines (SVM) are another powerful machine learning tool that can be used to diagnose melanoma. SVM is a supervised learning method that can be used in regression or classification applications. SVM is expressed mathematically as the process of identifying the optimal hyperplane by solving a convex optimization problem. The SVM decision function is based on the dot product of the input vector and a weight vector.

The following equation can be used to express the decision function in a binary classification problem.

$$f(x)=sign(\langle w,x\rangle+b) \quad (2)$$

Were, $f(x)$ *is the decision function.*
w *is the weight vector*
x *is the input feature vector*
b *is the bias term*

The result of the decision function displays the expected class (melanoma or non-melanoma). SVMs are helpful for medical diagnostics, particularly the identification of melanoma, since they can manage high-dimensional data and set challenging decision boundaries.

3.4. Deep Learning analysis

The last section of the research begins with the suggested Ensemble Regional Dense Neural Network (ERDNN) model being used to categorise the severity level of melanoma. The ensemble technique is used in the regional dense neural network to classify the different phases of melanoma into distinct classes. According to the suggested ERDNN model, the most significant classes are Akiec, Bcc, Bkl, Df, Mel, Nv, and Vasc.In order to analyse the accuracy, the proposed model is tested against a number of existing models, including the Linear Support Vector Machine (LSVM), Quadratic Support Vector Machine (QSVM), Cubic Support Vector Machine (CSVM), Medium Gaussian Support Vector Machine (MGSVM), Cosine K-Nearest Neighbour (CKNN), Weighted K-Nearest Neighbour (WKNN), Coarse K-Nearest Neighbour (CKNN), Ensemble Subspace Discriminative (ESD), Ensemble Boosted Tree (EBT), and Ensemble Subspace K-Nearest Neighbour (ESKNN). The Melanoma Severity Level Identification Process used in the Research Work is outfitted with the suggested ERDNN.

Proposed ERDNN Algorithm: Deep networks rarely have independently formed ensembles, most likely because training even a single network requires a large computational investment. The performance of deep networks has eliminated the need for ensembles of shallower networks; however, in our case, we would prefer to train and perform early-stopping on multiple deep networks rather than focusing all of our resources on a single network due to the diminishing marginal gains in accuracy with extended training epochs. We anticipate that the results of an ensemble approach will be better than those of a single model. Our group model uses the results as input.$s_c^i$for a class c ∈ C, normalizes them across the classes, and then marginalizes them across the models, starting from model i∈ I = {1,..., n}

The ensembles regional equation is substituted in the dense neural network split up for better accuracy and implementation speed. A dense layer in any neural network is one that has a high degree of connectivity to the one before it, meaning that all of the neurons in that layer are connected to every other neuron in that layer. The most often utilized layer in artificial neural network networks is this one.In a model, every neuron in the layer above the dense layer contributes to the output of the dense layer neurons, which multiply matrix-vector. The process of row vector of output from previous layers equaling column vector of output from previous layers equaling column vector of the dense layer is called

matrix vector multiplication. When multiplying two vectors in a matrix, the row vector needs to have an equal number of columns as the column vector.
The accuracy and execution time are tested using the same set of current models. In order to determine the precision, recall, F1-score, time, accuracy, FNR, and AUC, the confusion matrix for both the suggested model and other models that are currently in use is also measured. According to the final results, the suggested ERDNN Model performs better than the other models that were provided. For radiologists and surgeons looking to forecast the Melanoma Stage based on skin tone, the suggested ERDNN-based classification of Melanoma Severity Level may be the best option. The process used in the feature extraction and preprocessing phases is crucial to identifying the difficult ones. Another useful tool for improving the quality of the resource obtained is the convolutional ReLu for the activation function. One of the hybrid methods for analysing the severity level of melanoma that was derived from Deep Neural Network applications is the Ensemble Regional Dense Neural Network.

4. RESULTS AND DISCUSSION

The data must first be cleaned, preprocessed, and arranged before being input into an excellent model. Probabilities ought to naturally be the outcome. The ability to evaluate the efficacy of the proposed model greatly increases the likelihood that enhanced effectiveness would result in increased performance, which is exactly what the identification process requires. When classifying the differences between convolutional ethos and process using the activation function, the confusion matrix is crucial. A machine learning classification performance metric is the confusion matrix.

Table 1. Classification results using ERDNN on augmented HAM10000 dataset.

Classifier	Recallrate(%)	Precisionrate(%)	FNR(%)	AUC	Accuracy(%)	Time(sec)	*F*1-score(%)
LSVM	92.71	92.85	7.285	0.992	92.50	1303.8	92.78
QSVM	94.85	94.85	5.142	0.997	94.80	2400.4	94.75
CSVM	95.00	95.00	5.00	0.854	94.90	2868.5	95.00
MGSVM	92.85	93.14	7.142	0.995	92.60	4501.6	92.99
CKNN	61.71	73.14	38.28	0.910	62.20	562.0	66.94
WKNN	83.42	84.57	16.27	0.971	82.10	**530.7**	83.99
ERDNN	95.00	95.00	5.00	0.997	95.00	4118.2	95.00
EBT	62.00	62.22	38.00	0.855	62.80	69886.0	62.11
ESKNN	88.14	87.57	11.85	0.931	87.00	543.2	87.85

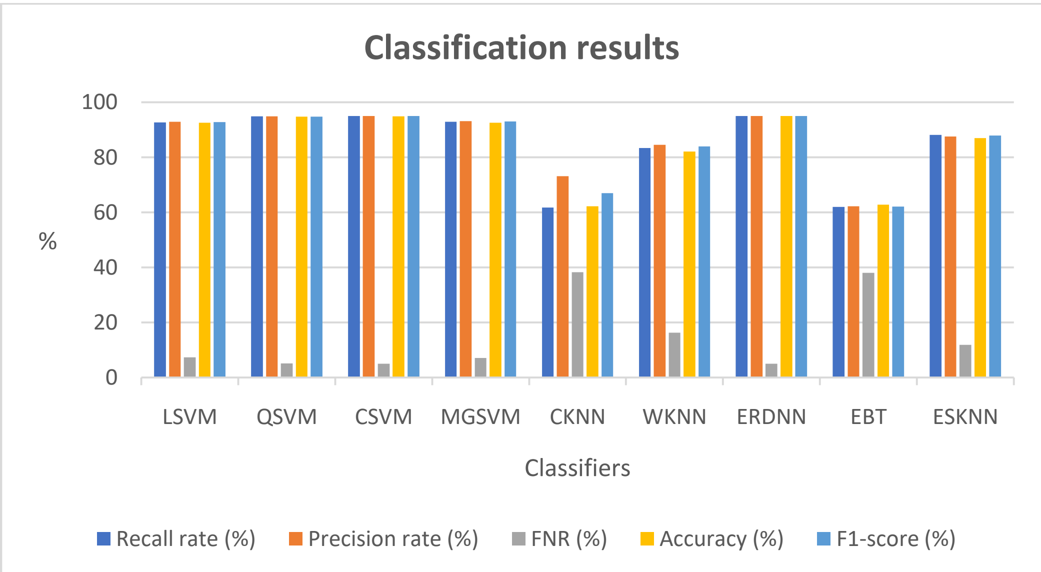

Figure 2. Classification results using ERDNN on augmented HAM10000 dataset

5. CONCLUSIONS

It can help dermatologists identify and track skin problems such as skin cancer early on. If skin cancer is detected early, a physician may be able to treat diagnosed skin lesions appropriately. The study project aims to classify melanoma cases in the dataset and identify the kinds of skin lesions shown in the collected images. The cancer is believed to have started in the cells that were identified as malignant and nascent from the collected photos. Converting the collected photos into formats suitable for simulations was the initial stage of the study effort. This approach also takes into account variations in mild, moderate, and severe skin-infected illnesses. The preliminary stages of the research process are thought of as the digital image processing setup. The method for selecting the features needed to identify melanoma in skin lesions is explained in this particular study paper. The phase of analysis makes use of the obtained results.In comparison with other current classification techniques, the suggested Convolution Rectifier liner unit (CReLu) is a hybrid machine learning technique intended to identify skin lesions. This proposed CReLu basically uses a deep neural network technique for user InterVision to mimic the results. It is evident from the study work's testing technique that the suggested CReLu outperforms other current algorithms. Compared to other current algorithms, this one performs significantly better in terms of accuracy and execution time.In order to forecast the severity levels of skin lesions, the last phase of the study work focuses on ensemble learning using the Neural Dense convolutional approach. The process aids in comparing the accuracy and time contains of the suggested model with other models that are currently in use. The proposed ERDNN's CReLu Coupled with Ensemble technique is essential for identifying melanoma presence in skin lesions.

REFERENCE

[1] Agnessa Gadeliya Goodson and Douglas Grossman. Strategies for early melanoma detection: Approaches to the patient with nevi. Journal of the American Academy of Dermatology, 60(5):719–735, 2009.

[2] Ahmed K, Jesmin T, Rahman MZ (2013). Early prevention and detection of skin cancer risk using data mining. Int J Comput App, 62, 1-6.

[3] Alan P Mangan and Ross T Whitaker. Partitioning 3d surface meshes using watershed segmentation. IEEE Transactions on Visualization and Computer Graphics, 5(4):308–321, 1999.

[4] Alejandro F Frangi, Wiro J Niessen, Koen L Vincken, and Max A Viergever. Multiscale vessel enhancement filtering. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pages 130–137. Springer, 1998.

[5] Bojarczuka CC, Lopesb HS, Freitasc AA (2001). Data mining with constrained-syntax genetic programming: applications in medical data set. Algorithms, 6, 7-0.

[6] Brian D'Alessandro, Atam P Dhawan, and Nizar Mullani. Computer aided analysis of epi-illumination and transillumination images of skin lesions for diagnosis of skin cancers. In 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pages 3434–3438. IEEE, 2011.

[7] Bulent Erkol, Randy H Moss, R Joe Stanley, William V Stoecker, and Erik Hvatum. Automatic lesion boundary detection in dermoscopy images using gradient vector flow snakes. Skin Research and Technology, 11(1):17–26, 2005.

[8] Chen LC, Zhu Y, Papandreou G, Schro_ F, Adam H. Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation. arXiv preprint arXiv:180202611. 2018;.

[9] Feng-Ying Xie, Shi-Yin Qin, Zhi-Guo Jiang, and Ru-Song Meng. Pde-based unsupervised repair of hair-occluded information in dermoscopy images of melanoma. Computerized Medical Imaging and Graphics, 33(4):275–282, 2009.

[10] Fernand Meyer and Serge Beucher. Morphological segmentation. Journal of visual communication and image representation, 1(1):21–46, 1990.

[11] Fernando ZT, Trivedi P, Patni A (2013). DOCAID: Predictive healthcare analytics using naive bayes classification. In Second Student Research Symposium (SRS), International Conference on Advances in Computing, Communications and Informatics (ICACCI'13).

[12] G Argenziano, C Catricalà, M Ardigo, P Buccini, P De Simone, L Eibenschutz, A Ferrari, G Mariani, V Silipo, I Sperduti, et al. Seven-point checklist of dermoscopy revisited. British Journal of Dermatology, 164(4):785–790, 2011.

[13] Germán Capdehourat, Andrés Corez, Anabella Bazzano, Rodrigo Alonso, and Pablo Musé. Toward a combined tool to assist dermatologists in melanoma detection from dermoscopic images of pigmented skin lesions. Pattern Recognition Letters, 32(16):2187–2196, 2011.

[14] Gilbert Strang and Truong Nguyen. Wavelets and filter banks. SIAM, 1996.

[15] Giuseppe Argenziano, Gabriella Fabbrocini, Paolo Carli, Vincenzo De Giorgi, Elena Sammarco, and Mario Delfino. Epiluminescence microscopy for the diagnosis of doubtful melanocytic skin lesions: comparison of the abcd rule of dermatoscopy and a new 7-point checklist based on pattern analysis. Archives of dermatology, 134(12):1563–1570, 1998.

[16] Giuseppe Argenziano, Iris Zalaudek, Rosamaria Corona, Francesco Sera, Lorenza Cicale, Gianluca Petrillo, Eleonora Ruocco, Rainer HofmannWellenhof, and H Peter Soyer. Vascular structures in skin tumors: a dermoscopy study. Archives of dermatology, 140(12):1485–1489, 2004.
[17] Hengameh Mirzaalian, Tim K Lee, and Ghassan Hamarneh. Hair enhancement in dermoscopic images using dual-channel quaternion tubularness filters and mrf-based multilabel optimization. IEEE Transactions on Image Processing, 23(12):5486–5496, 2014.
[18] Ilias Maglogiannis and Charalampos N Doukas. Overview of advanced computer vision systems for skin lesions characterization. IEEE transactions on information technology in biomedicine, 13(5):721–733, 2009.
[19] Mohammad Taghi BahreyniToossi, Hamid Reza Pourreza, Hoda Zare, Mohamad-HoseynSigari, Pouran Layegh, and Abbas Azimi. An effective hair removal algorithm for dermoscopy images. Skin Research and Technology,19(3):230–235, 2013.
[20] Nabin K Mishra and M Emre Celebi. An overview of melanoma detection in dermoscopy images using image processing and machine learning. arXiv preprint arXiv:1601.07843, 2016.
[21] D. Zhao, G. Yu, P. Xu, and M. Luo, "Equivalence between dropout and data augmentation: a mathematical check," Neural Networks, vol. 115, pp. 82–89, 2019.
[22] Perumal, S. and Velmurugan, T., Preprocessing by contrast enhancement techniques for medical images. International Journal of Pure and Applied Mathematics, 118(18), pp.3681-3688,2018.
[23] Bharathidasan, G and Arunachalam, A S; Pre-Processing for Early Detection of Breast Cancer using Machine Learning, NeuroQuantology, Vol. 20, (10), pp- 8423 – 8435,2022.
[24] O. Sevli, "A deep convolutional neural network-based pig- mented skin lesion classification application and experts evaluation," Neural Computing and Applications, Springer, Berlin, Germany, pp. 1–12, 2021.
[25] M. A. Khan, Y.-D. Zhang, M. Sharif, and T. Akram, "Pixels to classes: intelligent learning framework for multiclass skin lesion localization and classification," Computers & Electrical Engineering, vol. 90, Article ID 106956, 2021.
[26] J.-A. Almaraz-Damian, V. Ponomaryov, S. Sadovnychiy, and H. Castillejos-Fernandez, "Melanoma and nevus skin lesion classification using handcraft and deep learning feature fusion via mutual information measures," Entropy, vol. 22, no. 4, p. 484, 2020.
[27] A. Thilagavathy, Karuturi Hemanth Suresh,Katari Tejesh Chowdary, Meka Tejash,Vijayarao Lakshmi Chakradhar. "TextDetection based on Deep Learning", International Conference on Innovative Data Communication Technologies and Application(ICIDCA), 2023.
[28] Syed Inthiyaz, Baraa Riyadh Altahan, SkHasane Ahammad, V Rajesh et al. "Skin disease detection using deep learning", Advances in Engineering Software, 2023.
[29] Tammineni Sreelatha, M. V. Subramanyam,M. N. Giri Prasad. "Early Detection of SkinCancer Using Melanoma Segmentation technique", Journal of MedicalSystems, 2019.
[30] Arushi Pandit, Akshita Gupta, Madhulika Bhatia, Subhash Chand Gupta. "Filter Based Feature Selection Anticipation of Automobile Price Prediction in Azure Machine Learning", 2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON), 2022