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An Efficient Skin Cancer Classification Approach Using Neural Networks

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Abstract

Skin cancer is the most extensive cancer identified in the world and is highly contagious. Hence it is essential to prognosticate the disease at the earliest stage. The task is to forecast seven ailment categories with skin lesion images, containing actinic keratoses, melanocytic nevus, basal cell carcinoma, melanoma, and intraepithelial carcinomae, benign keratosis, dermatofibroma and pyogenic granulomas and hemorrhage. To accomplish the automatic categorization of skin lesions based on the disease, various neural networks such as Convolutional Neural Networks, Region-based Convolutional Neural Network and ResNet algorithms are used here owing to its fine-grained variability in the classification of skin lesions. The models are trained and assessed on dermatoscopic images collected from a cluster off publicly available datasets gathered manually. Initially exploratory data analysis is done over the images, followed by data pre-processing, augmentation, segmentation and extraction to contemplate the facts required to train the models and also to ensure the accuracy. This fully enhanced image is now fed into the algorithms where the features and bounded-regions are applied to get the convoluted layer. The model architecture generates a chain of layers to conclude on the output layer of seven neurons each indicating every class of disease. The presentation of the model is analysed based on various parameters such as precision, support, F1-score, accuracy etc. With these evaluation metrics a comparative study is done to judge the model behaviour. Also, the models are further assessed by making it to predict the class of disease of some random lesion. Hence the project is successfully created with help of requirement analysis, project plan, identifying features and functionalities, system validation and deployment. Thus, this application would act as the efficient need of the hour to obtain exact outcomes for the health care organization to act on instantaneously.

Keywords: Skin cancer, prediction, Convolutional Neural Networks, Region-based Convolutional Neural Network ResNet

1. Introduction

Skin malignancy is commonly seen in various people around the globe. It is caused by unrepaired DeoxyriboNucleic Acid (DNA) in skin cells that produce hereditary deficiencies or mutations on the skin. It inclines to progressively range over other body portions, so it is more curable initially, that is why it is more important to detect at the beginning stages. As per the World Health Organization (WHO) reports, the number of people who will be infected by skin tumor will increase up to nearly 13.1 million by 2030. As the incidence of skin cancer is expected to double and could increase at a quicker rate than any other categories of tumor, it has become a chief threat among humans. Initial diagnosis is a challenging task. On the other side, more treatment options are available for this.

Currently more refined equipment and highly qualified specialists are required for precise discovery of skin cancer. Dermoscopy is a dedicated method for finding high-resolution magnified descriptions of the skin, by directing light and eliminating surface skin reflectance. Though, if the clinicians are not well qualified in identifying the type of skin cancer from dermoscopy images, numerous patients will be misdiagnosed. So, there is a mandate need for computerized image investigation systems to recognize the kind of skin cancer from dermoscopy images. The possible glitch even otherwise is stimulating the characteristic of every kind, because of the enormous differences of skin diseases in terms of shape, size, location, color, texture etc. of the dermoscopy images, and the graphical resemblance of non-cancerous and cancerous lesions.

Thus, the proposed application aims at predicting the class of skin disease with at most accuracy using multiple deep learning approaches such as Convolutional Neural Network (CNN), Region-Based Convolutional Neural Network (R-CNN) and ResNet. With RCNN, the initial phase of the track is the generation of boundary-based region segmentation in an image which could be an attribute of a particular lesion class. This selective exploration procedure works by producing sub-regions of the image that could be appropriate for a type of lesion - based on multiple feature-based attributes, iteratively joining similar regions to form lesions. The proposed approach gives lesion samples of various classes uniquely with different scales. With this approach, the implementation had generated about 2000 group liberated region proposals typically designated by bounding boxes for every distinct image. This well segmented approach outstands in classifying the infected area to each type of cancer that is intended to handle. The bounded image is then passed to the proposed CNN approach with necessary layers for the algorithm to train and analyse the characteristic of every kind and add the novel classification layers to the network to complete the classification to the output kernel. The layers are setup to categorize the number of objects the network should notice plus an additional background class.

CNN is selected here because it provides high precision in image processing and is best suited for image processing. CNNs can be considered as a package of loaded convolutional modules, and every module usually contains of three layers; convolutional layers, pooling layers and dense layers. It applies a sequence of convolutional filters to the fresh lesions to mine the contrariety in every level of data. Primarily, CNN procedure can be confined into four pivotal steps. The top most layer is the input layer that explains the simple and basic information about the infection is understood. This layer then gathers the facts and directs it to the subsequent layers which is further passed on to the pooling layer. Pooling layer intends to group the information into a structure with either max pool or min pool. The pooling layer refers the augmented data after pooling for smoothing to one of the filter layers that sequentially straightens and transforms the information to 1D vector. This fact then gets into the thick layer which is strategically multiplied to accustom to the class wanted based on the information received over the previous layers. Features such as lines at dissimilar angles and outlines identical human faces, that can be involved for categorization in numerous instances are ranked.

For ResNet algorithm, enduring learning is presented and was selected as a constituent model of the ensemble. It makes a penetrating network with a huge sum of layers that maintain the learning residuals to tie the predicted labels with the actual labels. The pivotal concepts of the model are the convolution and pooling layers that are completely linked and loaded one behind the other. The uniqueness among the layers of the residual network distinguishes between the typical and the residual network. In such pre-trained residual networks, augmented images are passed to determine the type of cancer.

This paper aims to forecast the type of skin infection as feasible cause with computerized prediction of class of skin disease with lesions that is reassuring in the medical field for clinicians. To cater the proposed aim, multiple models such as CNN, R-CNN and ResNet are used, discussed and applied on the data set for training, validation and testing accordingly. This project also depicts the features that contribute than the others to expect the higher precision. This concept may exclude the expense of different trials of a patient, as all the features may not donate such a considerable quantity to anticipate the proposed outcome. Also, with such digitalized approaches it is certain to conclude on the category of infection.

2. Literature Survey

The job of categorizing the skin cancer by means of ECOC SVM, and deep CNN [1]. An existing, and pre-educated AlexNet is used in mining skins. This showcases parameters such as accuracy, sensitivity, and specificity. The request for an intellectual and rapid categorization arrangement of skin cancer by means of modern highly-efficient NN is attempted here. However, an enhancement in sorting superiority could be attained by accumulating clinical data such as age, gender, race, skin type, and anatomic location as inputs for the classifiers. Thus, this aspect aids in better decisions for dermatologists.

Pomponiu et al [2] used only 399 images from an ordinary camera for the categorization of malignances versus non-threatening elements. The lesions were then categorized with a KNN classification approach by cosine distance metrics. The procedure wasn't verified with a self-governing test data cluster; only a cross-validation was done. Along with the non-existent self-governing test data cluster, it is also pivotal to notice that the region of concentration for every lesion has to be physically marked.

In Nasr-Esfahani et al [3], a bi-layer CNN was accomplished origin owing to the peculiarity of images. Of the cluster, 136 images were used to equip the model and the testing of data was limited to thirty-four images which is small in number. Lesions were collected from the open image cluster of the Department of Dermatology of the University Medical Center. This procedure acquired sensitivity up to 81%, a specificity piling to 80%, and an accuracy of 81%. Though, the outcome would be perceived systematically, the test data cluster was very inadequate.

In one of the citations, Attia M. et al. [4] discusses about lesion classification as the only prime concept. The authors used NN based approaches to improve a boundary region split system.

The anticipated architecture encompasses seven convolutional layers that describe the self-encoder part and four consecutive and retentive layers. Collection of almost up to 900 images were put together from ISBI 2016 which was used for calculating the results. A Jaccard Index of 93% and bounded region classification's accuracy of 98% were obtained.

Certain researchers like, Li Y. et al. [5] also used Deep Learning methods to perceive cancer. Lesion Feature Network and Lesion Index Network, the two forms of CNN developed to equip the cause with necessary were utilized to achieve the attribute mining, boundary-region categorization, and alignment paces. Scheming of the distance cosine map is then accompanied to aid the inferences. To extract the enhanced features after data pre-processing, the proposed Lesion Index Network was considered. When Lesion Index Network is taken, the attained accuracy for lesion segmentation and categorization was 91.2% whereas the attained Jaccard index was 75.3%. The evaluation was appraised further with metric such as sensitivity and precision (69.3% and 42.2%). CNN enhancement research was achieved by Zhang L. et al. [6] in 2019.Determination of this research was to increase the preparation of layer weights and biases by relating a meta-heuristic technique. In order to diminish the learning error, the researchers projected the whale optimization algorithm.

The integration of meta-data and lesion attributes are combined to enhance the performance using an architecture loosely based on CNN is implemented to segregate lesions based on certain type [7]. The possible advantage in this arena of study is by assessing the categories of patient data, the process in which the lesions are encoded and amalgamated with the mapping to the necessary attributes, and the incorporation on the model behaviour. It involved certain alterations in the difficulty that the re-worked patient data were administered with deep learning procedures both before and after fusing them with the image traits to a joint classifier.

Researchers in [8] targets to offer a procedure for scheming a melanoma categorization structure grounded on CNN and a conventional new regularizer for adjusting the difficulty of the classifier to, make it more precise. The upshots are more precise when compared with other works from the various implementations. Likewise, alternative study [9] suggests a skin analysis structure based on a grouping among CNN and efficient classifiers precisely revolving on texture attributes.

In [10], SVM model is used and attained an accuracy of 90%, where the implementation being a bit dissimilar from CNN design having pre-trained images and transformed into 1D array and educated with SVM model. In [11], CNN was employed with a series of input and output layers. The group dimension was 20 and number of epoch size was 25. The accuracy achieved was up to 70%. [12], speaks about YUV technique with 300 images and the cluster being classified with 80% for training and the remaining for testing. When further trained using SVM, a complete accurateness of 86.7% was attained.

The study identified lesion analysis and classification systems by means of methods apart other than CNNs. A sample of that methodology is reflected [13], which intends to propose a solution for designing a lesion segmentation system based on the ABC procedure for achieving an ideal threshold rate for lesion discovery for the boundary-region classification phase. To summarize, the system is a collection of three modules: the pre-processing, the implementation of the ABC procedure to discover the finest threshold that is to be identified for class detection, and the separation element.

3. Existing System

In the human body, skin is anticipated to be the largest organ. In this modern era, skin ailment is the prominent reasons for cause of most infections and newer complications. Skin disease may occur due to unhealthy lifestyle, exposure to sun, Ultra Violet (UV) rays etc. According to WHO more than 10 billion people are affected because of coronary skin ailments each single year all over the world. A strong lifestyle and primary discovery are only methods to avoid the skin associated ailments.

In India, medical results are often made based on clinician's skill rather than on the understanding of rich data concealed in the database. From a dermatologist perspective, the suspicious skin has to be visually examined, and then if it requires more study the image is captured in a high-resolution camera that reviles hidden details of the layers of the skin. The detection is directly based on the experience of the physician which has not standard accuracy. This practice leads to unwanted errors and high cost which affect to service provided to the patients. The core challenge in today's healthcare is establishment of best excellence services and operative precise analysis. Even if skin ailments are found as the main basis of demise in the world in recent years, they are also the ones that can be measured and accomplished effectively. The complete precision in management of ailment lies on the appropriate time of discovery of that ailment which cannot be in physical processes.

Technology based skin tumor categorization can be constructed as an application by intense NN, typically produce estimates-based solitary on images of skin lesions. Regardless of offering favourable outcomes, it's conceivable to attain advanced performance by considering patient demographics, that remain significant evidences that medical specialists take in the course of skin lesion filtering manually. Using deep learning models, the difficulty of uniting metadata attributes and imageries implemented is tedious to skin cancer classification. One of the approaches is done using Metadata Processing Block (MetaBlock), that makes use of metadata to keep up data classification by improving the most appropriate attributes taken out from the imageries during the course of categorization pipeline. It associates the technique with two added grouping methodologies: the MetaNet and other related to attribute appending process. Outcomes obtained for two dissimilar skin lesions achieve well than the other grouping methods in 6 out of 10 situations. However, there are numerous digitalized approaches projected to attain a solution, hence there is scope for additional enhancement in current diagnostic procedures.

The following are disadvantages of existing approaches

- In the existing system, a lot of paper work is involved (in the form of medical reports) which involves a lot of time and money.
- There are probabilities for wrong diagnosis of the disease. This would cause a lot of discomfort for both the management as well as patients.
- The results once calculated may not be consistent (i.e) not all classes were predicted accurately.

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4. Proposed System

NN based algorithms have provided better results for attribute withdrawal from pictures and recently accomplished excessive victories in image handling presentations. Among various features, the chief one of CNN count on the architecture with deep layers that lets the taking out of specific features from lesions at numerous stages of extraction. Since CNN makes use of comparatively few preprocessing when compared to other algorithms of image classification (KNN, SVM etc.), which are encouraged through various biomedical systems. CNN is applied for the analysis of diseases abundantly. With RCNN, the prospective objects in an image are identified by the algorithms using segmentation process. Based on some criteria like color, texture etc, nearby sections are grouped which are alike each other. Smaller number of segments are formed by grouping pixels which is done by region proposal algorithm. It decreases a lot of patched images which is to be classified. The above processed segmented images differ in scales and aspect ratios. Owing to such features and also backed-up by residual algorithms such as ResNet the procedure aims to classify various skin lesions based on their category with comparative analysis of each model.

To summarise, in this project, based on the seven types of cancer creating unique CNN, R-CNN and ResNet architectures dermoscopy depictions are divided. As the effort educates the impact of the construction of multiple NN architecture which is the combination of sequential layers) and to construct a improved CNN, R-CNN and ResNet model, it is trusted to put forward to previous discovery periods, that improves probabilities of efficacious handling of injurious cancerous cases. Thus, this architecture aims to detect the classes of skin cancer efficiently with accurate results and evaluate the opinions to perform prediction with confidence. The overall procedure is represented in Fig 1

Fig 1. Overall Process flow

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CNN Architecture

CNN has several convolutional layers trailed by one or more fully-connected layers. The model accepts the inputs in the form of images, it is evident to encrypt some properties into the design. This makes additionally well-organized function with a less amount of properties in the system. The next benefit of CNN over fully associated networks is easiness to equip the model. The major functionalities that can be observed in CNN is given below

- Convolution
- Non-Linearity
- Pooling (Subsampling)
- Categorization

An image, is always a collection of pixels. It is categorized into three as red, green and blue. These RGB values confine in a wide range from 0 to 255. CNNs consist of multiple layers where each layer transforms an input layer to an output layer with differentiable functions. Three layers that constitute to the construction of CNN architecture are convolutional layers, pooling layers and fully-connected layers. Figure 2 shows the discussed architecture.

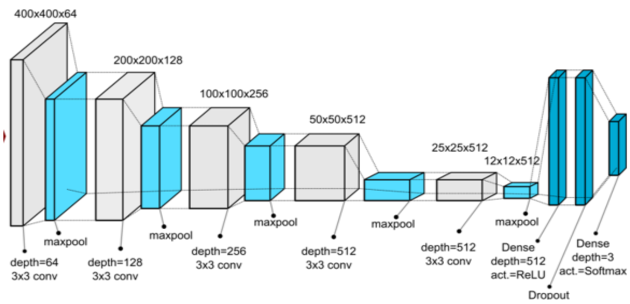

Fig 2. CNN Architecture

R-CNN Architecture

The major difficulty with the above standard convolutional network is that the dimension of the fully connected layer is capricious, implying that the number of incidences of the malignance that appears in the lesion is variable. To overcome the drawback, it would be better to segment regions of interest from the image as boundaries and use a CNN to classify the presence of the infection within that region. The above approach constitutes the concept of Region Based Convolutional Neural Network (R-CNN). Here the dataset considered is split into three categories as train, valid and test sets. The dataset used here is labelled in nature, thus making the algorithm to supervised to understand and analyse the characteristic of every disease.

The initial step as a part of the model is to generate the sub-segmentations and bounded regions of the image that belongs to the lesion based on its attributes and repetitively group similar regions to understand the type of each class. With the segmented region of images done, the necessary flips, zooms and rotate operations are carried out to generate a processed and augmented image which is then fed to the model architecture.

The model architecture then generates a series of layers to train and equip itself to infer the type of cancer. With the initial layer fetching the trained image as input, a group of hidden

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layers is generated each constituting to the segmentation done while pre-processing. Once this labelled data and region-based image evaluation is iterated on the model over the necessary layers, the model passes the output layer with seven kind of outputs each constituting to a class of disease. With the output layer obtained from the model, the results are inferred with the valid and test datasets, where the valid set is used to educate the model if the actual and predicted results aren't same while the final model is tested with test data set.
Thus, based on the results from the above algorithm, the prediction of every class of disease, is done. To study the algorithm's understanding, one can pass on a random class of lesion to it so that it can calculate and analyse the type of cancer. Figure 3 depicts the discussed architecture.

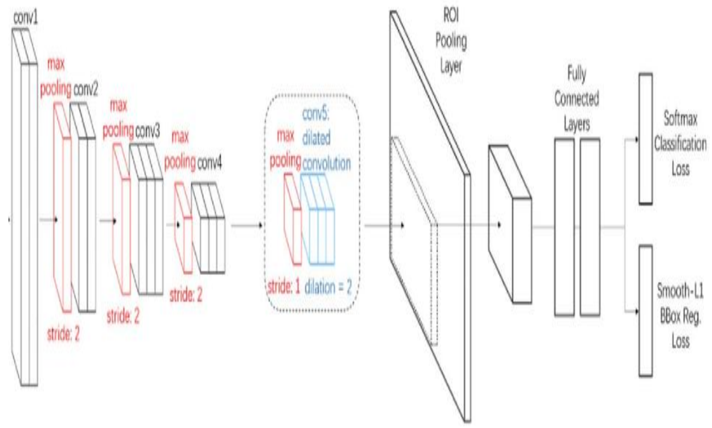

Fig 3. R-CNN Architecture

ResNet Architecture

ResNet is a transfer learning-based model that involves the usage of sequential neural networks. ResNet involves the combination of residual clusters used greatly to resolve transient deprivation and also reduce aggregate parameters. Residual Networks model is a two-step process. Based on image segmentation done earlier, residual network is built with appropriate filter and feature map to understand the characteristic of every lesion. With this built-in architecture batch normalization is involved after each filter added layer and before ReLU activation function. The process is set to accommodate the lesions with multiple projections and dimensions.
This approach was attempted to compare the proposed system with an extension of one of the base paper approaches. In this process of image classification, the augmented images are fed, post which the training of the model to accustom our data is done with the help of convolutional layers, normalization practice and activation functions. The above approach is then evaluated with the parameters such as accuracy, precision, recall etc. Figure 4 depicts the discussed architecture.

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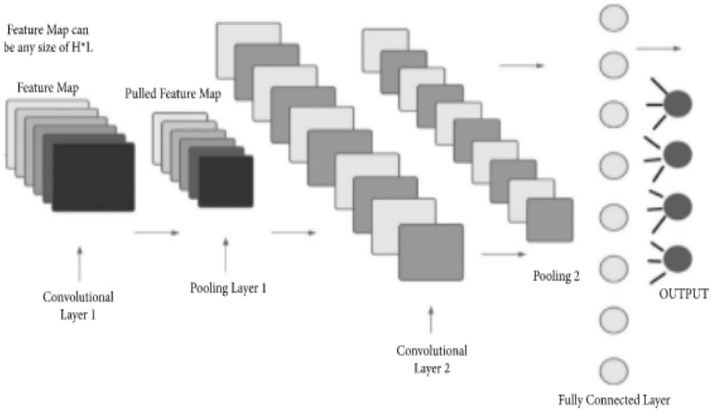

Fig 4. ResNet Architecture

The advantages of proposed approach are given below

- The proposed system aids in efficient decision making for the doctors in the diagnosis.
- Based on the skin lesion images collected the likelihood of patient getting a skin malignance and its type can be precisely found.
- The model is educated with a relatively large dataset so as to predict the relevant output based on the factors.
- The accuracy and precision parameters are compared with all classes of diseases individually so as to ensure the correctness of output predicted.
- The algorithms outlast the existing feature in its finesse in detecting the class of infection and the results are ascertained because of the comparative analysis with multiple algorithms.

5. Results and Discussion

This section describes the evaluation metrics implied to analyse the performance of the implemented model.

The Accuracy Score:

Accuracy is used as a measure to proportionally compare the number of correct guesses made to the total number of input lesions. Itis one such metric to study the performance of the set of algorithms involved with the given data correctly.

Accuracy Score = (TP + TN)/ (TP + FN + TN + FP)

The Precision Score:

Precision, is an evaluation metric that gives the degree of the positive prognostic value, as a fraction to the positive results which is also a true positive value.

Precision Score = TP / (FP + TP)

The Recall Score:

Recall is the grade of proportion between the number of correct samples rightly split as the correct guess to the aggregate count of correct samples. This metric is a measure involved to indicate the algorithm's ability to make the right guess on the correct samples.

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Recall Score = TP / (FN + TP)

The F1-Score:
F1 score is a combination of precision and recall. Precisely, combination of numerical mean of recall and precision can be characterized as F1-score.
F1 Score = 2* Precision Score * Recall Score / (Precision Score + Recall Score)

The Confusion Matrix
A confusion matrix is a grid whose purpose is to describe the ability of the proposed classification algorithm on a set of test lesions for which the positive degrees are explicit. It is used to pictorially portray the model performance.
To analyse and understand the behaviour of the algorithms and to ascertain the classification done over the results a performance study is made. From the understanding, it is inferred that R-CNN has outperformed with highest evaluation metric value, to have accuracy sight up to 99.5%, followed by CNN with 88.2% and ResNet values up to 85.7%.

Table 1. Comparitive Performance Analysis

	RESNET	CNN	R-CNN
ACCURACY	85.7	88.2	99.5
PRECISION	64	79	86
RECALL	33	61	79
F1-SCORE	43	61	78
SUPPORT	22	35	68

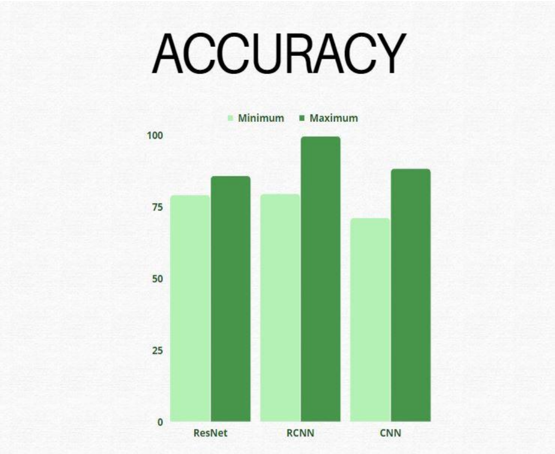

Fig 5. Comparitive Accuracy Plot

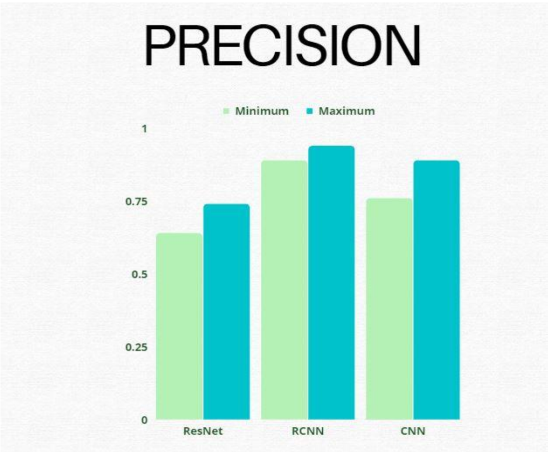

Fig 6. Comparitive Precision Plot

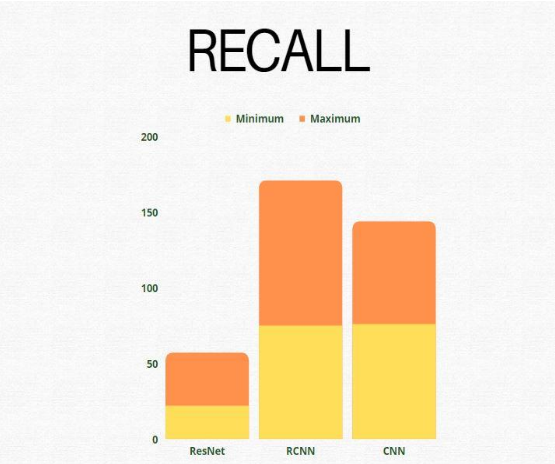

Fig 7. Comparitive Recall Plot

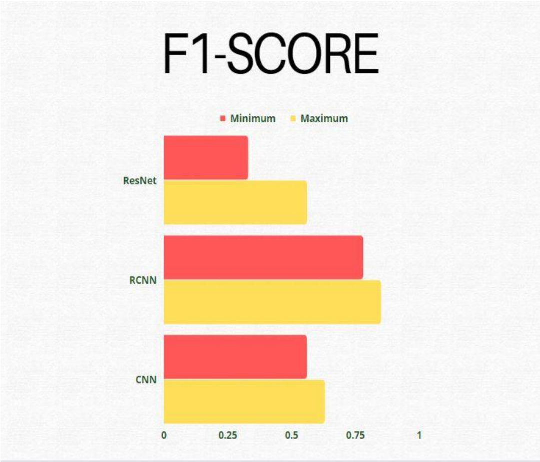

Fig 8. Comparitive F1-Score Plot

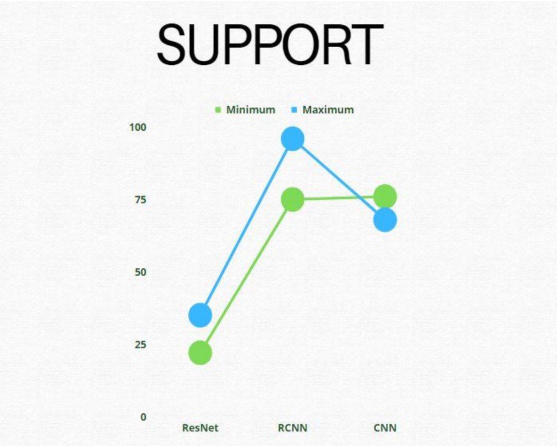

Fig 9. Comparitive Support Plot

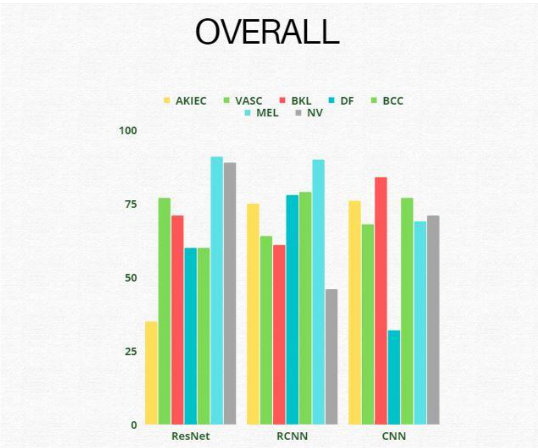

Fig 10. Overall Comparitive Plot of Seven Classes

6. Conclusion

Since skin diseases are one of the primary cancers that affects multiple cases every year all over the world, an application developed with the help of propitious methodologies such as deep learning to perform initial prediction of skin diseases will have a profound influence on the general public. Thus, the application would help the end users get a preliminary understanding about the type of infection on their skin. This will tell the user if they are at a risk and if they need to visit the doctor. Initially data analysis is done followed by data augmentation. This clean data at first is fed into the base layer which then handovers it to the concealed layers, and interconnection among these two layers allocate loads to every input arbitrarily at the primary point and then bias is added to every input neuron and subsequently, the weighted quantity which is a grouping of weights and bias is handed over the activation function. Activation Function has the accountability of which node to fire for attribute mining and lastly output is executed. After getting the output model it is associated with the original output and the error is known.

To enhance this procedure, certain profound techniques were implemented via ResNet and RCNN algorithm to cover the radii of all possible behaviour to ascertain our results. Thus, the application is successfully created with help of requirement analysis, project plan, identifying features and functionalities, system validation and deployment.

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