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Melonoma Cancer Stage Detection Using Machine Learning

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Abstract: Melanoma skin cancer, which is fatal, is a result of formation of a malignant tumor originating in melanocytes. Leukoderma is a non-cancerous disease and carcinoma is cancerous disease out of which melanoma is the most dangerous one which occurs due to pigment making cells, melanocytes. While there are many types of skin cancer, melanoma is particularly dangerous and accounts for approximately 75 percent of skin cancer deaths. Looking at the survival rate of patients with data derived from the analysis of the patients in the preceding five years, the results reveal that only 15% of the patients' survival has received chronic treatment. It is actually in a manual system. With regards to the mole, it has roughly about six of the maximum colours so the issue is the image, it has several shades and the human eyes cannot easily recognize it. For early diagnosis of melanoma cancer and to prescribe treatment at an early stage, required machine intelligence algorithms can be utilized. It assists in decreasing the work load on specialists, improving the rate of diagnosis, enhancing the time and reducing the clinical expenses. The purpose of this paper is to identify and eliminate skin cancer before it is too late and so reduce the mortality rate

Keywords: Melonoma, Tumors, Dermoscopy, Machine Learning, CNN

I. INTRODUCTION

The skin is also characterized with the function of heat since it is as part of a body's heat acclimatization as well as playing the role of protective shield of the body and the sun [1].

Skin diseases since they are many may develop in patients and some of them may be genetic and lead to malignant tumors Skin Diseases may develop in patients and some of them are genetic and lead to malignant tumors. Squamous cell carcinoma is one of the cancers of the skin that can have an impact in a patient's survival that is why it is among the skin cancers that include melanoma and basal cell carcinomas [2,3].

The three all together are believed to account for over three percentage of mess cancer incidences in the entire global population. It is estimated that 5 million plus cases are diagnosed every year, which includes melanomas [4]. Skin cancer can be fatal – one of the types of cancer that are very dangerous is melanoma: This immune reaction therefore occurs in the layers of the skin, hair, eyes and also in the melanocytes where they form malignant tumors[5].

Melanocyte tumors are normally black or brown but can be red; pink or even purplish [6]. A study co-authored by a British university states that 86 percent of the melanomas are caused by the type of nutrient producing rays called ultraviolet (UV) rays. For example, if a person got up to five sunburned, then this is the signal that the risk for developing melanoma will increase two times [4]. We also understand that melanoma results in skin cancer, however, individuals with a fairly pale skin complexion are some of the most vulnerable to the disease. Nevertheless, this skin cancer is easily cured once formative signs have not developed, and the melanoma is diagnosed early enough [7].

Classification is done through biopsy and is usually slow and sometimes even inaccurate compared to other diagnostic techniques. Among the elaborate methods which the dermatologist cannot afford to leave out in skin evaluation are the morphological and dermoscopy measurements.

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When the skin lesions cannot be seen at a macroscopic level, dermoscopy enables assessment of hundreds of aspects of lesions that could not be investigated earlier along with the visualization of deeper skin tissues, thus enhancing skin examination [8]. Radiology of skin is involved in enabling it to diagnose skin cancer and the use of images of the skin. Deroscopy is used in the diagnosis process of skin cancer to obtain dermoscopic images. In the last several years, after the development of computer vision and digital image processing, they have become indispensables to reduce the time spent on the visualization process and increase the elimination of errors up to a significant minimum [1].

Some past works focused on studying about the use of imaging features in CAD in terms of non-melanoma tumours [9] Similarly, in [10], the focus was made towards using deep learning in order to predict the characteristics of dermoscopy image of melanoma. Skin cancer is easily distinguished by forensic imaging thereby helping dermatoscopists. In fact the CV algorithms and the aspect of digital image processing enhanced over time and the strikes of human errors or minimized. Combined with computer processing of such images and cooperated with AI can help dermatologist sense the existence of melanas, and thus enhance the perception of melanoma and reduce the fear of biopsies in such cases [11]. CAD method has earlier been used in diagnosing cancer and another one was done recently[12][13].

Aggregated from the previous sections, a set of features that are traditional aspects of computer vision are applied to determine the size, colour, texture of the cells to detect cancers. However, it is difficult to separate or sort the images based on the placement of the aforementioned features because more than one image may have these characteristics. About two or three decades back, the mathematicians and scientists were employing the traditional methods to solve these kinds of problems, today, AI is solving these. The research in the area of skin cancer screening is still current [14], and deep learning has been applied to the problem of tumor recognition from dermoscopy features in images [15]. In the sense, the layers of CNNs possess the abstraction capability to heuristically determine the semantics and patterns in each and all the behaviors, patterns of edges and shapes. That is why this method enhances its accuracy in diagnosis of skin melanoma, at this [16]. Due to the severity of NT, there are several techniques available for diagnosing cancer, and this has made the CNN based diagnosis paramount in current practice [17]. All of CNNs provided higher results in both of the diagnoses as compared to all the experts, It was also explained that awareness could be helpful both for the skin cancer types and dermatology specialists [18].

II. LITERATURE REVIEW

This is an ideal observation since detection of melanoma can be given an appraisal based on many fronts of which diagnosis forms a core focal point for medical treatment. There are several techniques and steps taken in the distinction of melanoma from benign skin tumors. Some dermoscopy images of DSSs make decisions or help doctors with decision making, by using features in dermoscopy images used to differentiate between benign skin lesions and malignant melanoma. This was with the intention of understanding which of the many available methods to apply in skin cancer detection through the use of deep learning from the various papers that have been written.

Systematic literature review is a process of integrating the assessment of all the published documents which has been published in a particular format that has been ordered by means of the laid down evaluation criteria. The surveys contribute to the improvement of the existing knowledge we have in the related technique which is used often for development. While reviewing literature survey which summaries with the related research papers on skin cancer detection CNN is highly recommended for the detection of stage 1 and stage 2 of Melanoma skin cancer.

Recorded skin diseases, inclusive of cancerous ones, can be diagnosed via CNN in their early stages, and some of cancerous diseases include Melanoma and focal cell carcinoma A There are various factors that influence accuracy of detection of forged documents. Recently, machine learning techniques have been used with more often in the overall field and concepts such as image or concept processing known as Machine Vision has been used in many health related operations. Identification of skin diseases including Melanoma at an early stage: A current strategy proposed within this study [9] includes the use of machine learning approach on images – image processing.

A typical CNN network architecture is shown in Figure 1 below. In the CNN of this study [9], there is an updated whale optimization technique that has been used.

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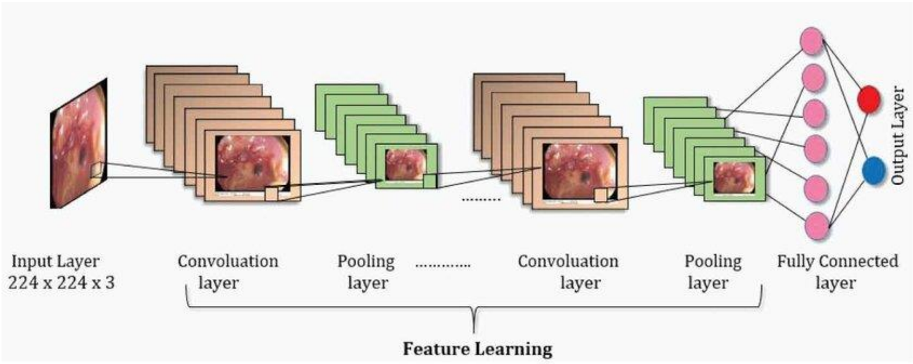

Fig.1 CNN Architecture

B. One of the types of models has a name contains the name of the method used for training – Support Vector Machine(SVM).

SVM is among the many efficient supervisory understanding methodologies broadly utilized by datamining without limitations. that may be used for learning and used in a system and this comprise of regression and classification problems. As mentioned in the figure 2 below, the general objective of SVM algorithm is to create a boundary or a hyperplane that defines separation of n-dimensional space to classes in such a way that categorization of data points could be done at subspace and higher speed, which is mostly and easily achieved. In applying the term “hyperplane” on this ideal decision boundary. Choosing outcomes & points, / vectors for forming the hyperplane is the work of SVM. Vectors of support are used as stated, The approach was used to describe these extremities hence why it was called the Support Vector Machine. Where in deciding between yes or no implanted in deciding whether a form of cancer is present or not based on the certain image, SVM uses the name Images or objects under study, while the class labels for images have to be oriented.

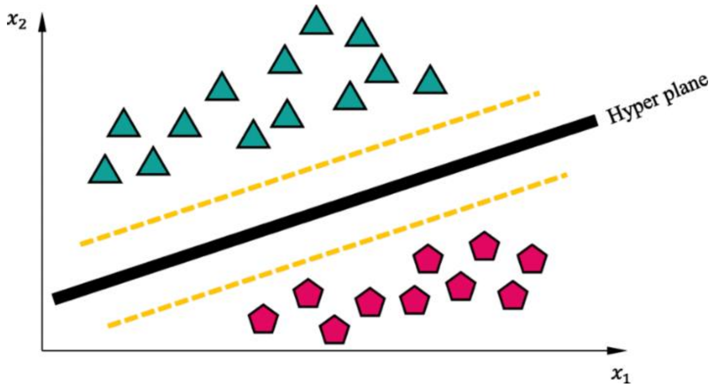

Fig.2 Data seperated into two classes using hyperplane

C. Lightweight Convolutional Neural Network:

- So far, specific operational CNN-based approaches have achieved some success in the sphere of melanoma’s fully automatic recognition [11] –[20]. At the same time there are less number of researchers working with this interesting phenomenon of a technique that challenged them previously when it was attempted to automate the detection of melanoma which led to the invention of deep learning models know as lightweight CNN [21] – [23] Besides, reducing the counting reconnaissance of the components of the model also improved the identification of skin diseases up to great extent in our model. For when we want to do AN fully end-to-end large lesion boundary delineation, we introduced the full convolutional semantic segmentation network with light model and U-net based network.

III. PROPOSED SYSTEM

1. Diagnosis of the stage of melanoma cancer is often a difficult task, as it involves analysis of numerous This is why the focus of some researchers was on a task to implement the detection of melanoma automatically which in turn led to the creation of deep learning models called lightweight CNN [21][22][23] these models reduce the number of model’s parameters, and at the same time enhance the capability to identify skin diseases.

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In this task, machine learning approaches can be of much help for they learn from the clinical data and are able to bring out the patterns and relations between the data on its own CNN algorithm which is amongst the deep learning algorithm was used to develop our model. The current structure of the proposed system architecture can be illustrated as follows: Available detection methods include the following. Proper identification of the malignancy of melanoma and accurate patient's diagnosis highly depend on the early identification of the changes in the development of the disease. For benign skin lesions and melanoma, there are a number of strategies of classification and treatment procedures. These are the following structures used in the proposed algorithm within the CNN's SMTP architecture. The layers encompassed by architecture are the Input layer, Convection layer, Rectified Linear Unit (ReLU) layer, Pooling layer, ReLU Fully Connected layer, Softmax Fully Connected layer and the Loss Function layer.

2. CNN provides the set of neurons that is one of the most critical deep networks of neurons that are successfully applied in the various fields of computer vision processes. A high-level representation of the architecture of the system is depicted in the following figure: Figure 1. The device is applied for picture classification, which involves compiling a set of input pictures, and image recognition. For classification, here, we utilized the ISIC2019 dataset. What CNN allowed us for is the collection of some data, data preprocessing, the training and evaluation of the model, deploying the model, and finally feature extraction. ReLU is a basic type of 'activation function' that rectifies the input signal or input data to produce an equal or higher level output signal. In the CNN model, an image and passed through layers of a convolutional filter which assists to get higher features of the image. These kinds of characteristics that are extracted are referred to as features and are then run-through a ReLU which is an activation function that makes it easy to introduce non-linearity to the model and equally beefs up the ability of the model which makes it easier to learn complex patterns. ReLU is fast and can be implemented; saving an enormous computational effort. Implementing it into a model adds non-linearity into the model, enabling the model to learn about other features and dependencies in the data. We were able to utilize the model with activation function ReLU that assisted in the increase of accurate predictions and made the model more efficient. Pooling is a function that is usually implemented in CNN used in various tasks such as identification of skin diseases with an application of image processing. The motivation for pooling is to reduce the amount of data in feature maps while preserving the necessary information. The input image goes through several convolutional layers in detecting skin using CNNs that help in extracting features like edges, corners and textures and so on.

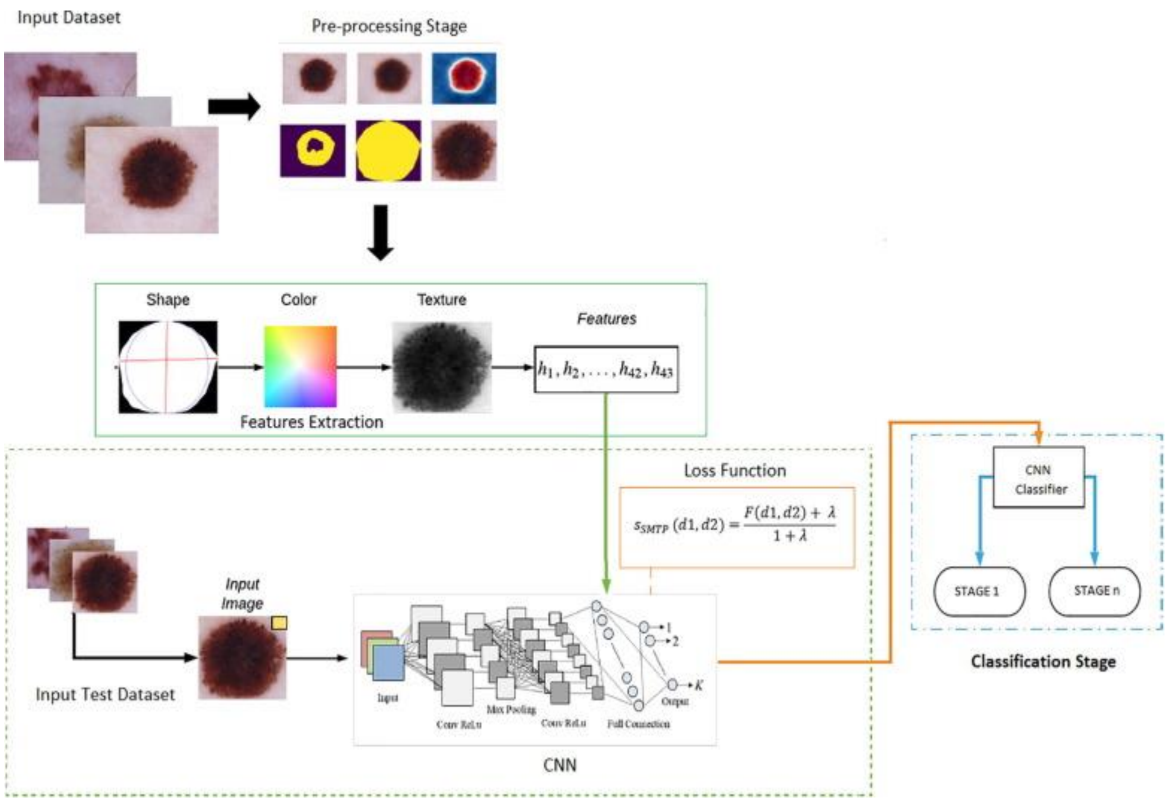

Fig.3 System Architecture

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The activation function called ReLU is a linear function that is explained subsequently in consecutive sections on frequent bases. The function returns the input value if the input value to the function is a positive value if the value input to the function is a negative value then the function returns zero. This is mainly because it is easy to implement, sufficiently computationally efficient for the deep learning models, and has been tending to improve the performance of neural networks' convergence and generalization. In a CNN for skin cancer diagnosis Convolutional Neural Network. The activation function called ReLU is a linear function, which is discussed successively in this paper at frequent intervals. The input value is returned when the value passed to the function is positive otherwise; zero is returned and as we shall ensure the input to the ReLU activation function is guaranteed to be non-negative, then the model can learn very complex non-linear relationships between the features from the input image and the target label. In several image classification applications such as the identification of skin cancer, a number of studies have shown that it has been effective in improving CNN performance. Altogether, CNNs are one of the essential frameworks of the ML-driven skin cancer detection system, and when used in conjunction with ReLU activation and fully linked layers. The last layer in the CNN network is conversely present in the ML approach to identify skin cancer via the softmax activation function. The outputs obtained from the fully connected layer are passed through softmax to make it look like a probability distribution over all the possible classes. A softmax activation function is normally come before one or more fully connected layers in a CNN for skin cancer diagnosis.

The features are extracted through the previous convolution layers and can now be of higher dimensions and therefore the fully connected layers generates a vector of scores or logits of each of the potential classes with each score indicate the strength of the evidence.

These scores or logits are then passed to the softmax activation function in order to process them to a point where they may be described as a probability that sums to one. Each element of the output vector represents the probability that the input image is from any specific class in the system. Especially useful in multi-class classification issues such as distinguishing different skin diseases including skin cancer like melanoma there is a need to classify an image taken as input to one of many potential classes then the softmax function proves helpful. It ensures that the output probabilities are probabilistic, unique, and equal to one which enhances model evaluation. In conclusion, when identifying skin diseases such as skin cancer using CNNs and a choice of ML approaches, layer configurations must include fully connected layers with softmax activation.

IV. METHODOLOGY

A. Dataset ISIC can be defined as a dataset log [5] that provided a compilation of various datasets for skin diseases. This dataset names ISIC [6] was launched for the first time at the ISBI challenge that took place in the year 2019 with the name ISIC 2019. In ISIC2019, training and testing data are divided into different folders so that the folders are recognized as individual sections. There are 25,331 images that define Section B, and these images fall into eight subclasses, which are types of skin lesions included in the ISIC2019 dataset. It includes a class with outliers as well as the training dataset and the test dataset of 8239 photos.

Logically it means that there is a class that contains outliers in addition to the training dataset of photos and the test dataset that contains 8239 photos. It is containing some photos of melanoma lesion in nearly 30. One is malignant melanoma and 47 images represent 3% of the images that are identified as benign nevi. On melanoma or a melanoma trial basis, the experiments are conducted. The dataset currently has 81 attributes or properties as it is classified into binary and multiclass datasets. There are a total of 25331 pictures of a cancer type named melanoma: 650 more individuals died from melanomas greater than 1. 5mm, 5 471 melanomas between 0. 76 and 1. 0.5 mm in thickness, 2352 between 0.5mm and 2.5mm, and 16921 less than 5mm in thickness. 76 mm. Therefore, we employed all the features employed in the identification process to narrow.

B. Approach
The basic flow of the model training process is demonstrated in Figure 4 and explained below.
1.Data Pre-processing : Data enrichment Disposal of the entire ISIC 2019 dataset[6] in training as well as in testing images. Both are present in the form of colored 3D pixels carrying quantitative values of red, green, and blue intensities. To minimize the computational workload, the feature images are converted to grayscale, wight with the color feature images with 3-dimension pixels is then transferred to 1-dimension pixels. Before applying the median filter, the skin images after going through the conversion of color space to grayscale get additional noise. This method in this median filter involves changing all the pixel values in a picture through using median value of each of the neighboring pixels.
Equation 1 g(a, b) = median [a, b],(a, b)X - [2]

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Here X is the neighborhood pixel value and g(a, b) is a function which we get as output. The intensity variance of an image is minimized with the use median value from the neighborhood.

2) Breaking Down of Dataset:
The dataset is usually split into about two to three sections; this is advantageous when training the data on one part of the entire dataset while testing is done on the other part of the entire dataset. This way, we are feeding unseen information to our model so that it can learn what value it holds. This unseen data helps us to find out the extent to which our model is learned or trained. If the training of the model is correct then the Data provided to the test data set will be classified rightly else the accuracy will be low or there will be high error rate. In our case, we are dividing our dataset in the ratio of 7:5. Out of the entire sample size, 70% of the size is used as the training data while the remaining 30% of the size is used as validation data which will help in assessing the validity of the built model in order to achieve higher level of accuracy.

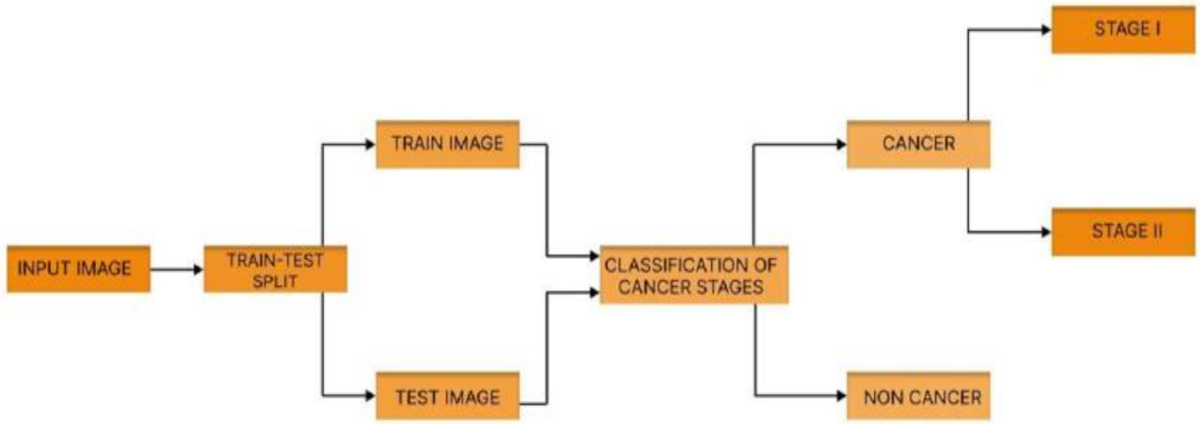

Fig.4 Flow of Model Training

3) Training : Training data is 70% of the entire dataset In the work related to data mining, this is the third step. Used deep learning algorithm known as CNN, is used so as to train the model. We use augmented data to train our model, this is an algorithm that is from CNN. CNN has several layers that perform data processing; the layers are used to train the machine learning model. The dataset that is separated and planned for utilization for training or learning is passed to the input layer.

The first layer takes the images given and then segregates all unnecessary colors and other elements that are too small and unreadable and sends the output to the next layer known as the convolutional layer. In this layer, the image pixels are filtered and transformed to the range 0-1 bit, which transform the colored image to the viually gray scale formats. The feature maps or the outputs that we obtain after passing through the convolution layer are actually filtered versions of the original image. This output enters the max-pooling layer of the designed model in this paper with the aim of performing feature reduction. In this layer, it scans the image and keeps the most clearly visible features.

In this layer, the rest of the processing and filtering usually take place and the resulting data is passed in the output layer. A particular activation function known as ReLU is employed while training with the CNN model. This model training is carried out in a batch-wise manner and its batch size is 32, which in a way provides that after the model processes every batch of these images, the weights involved are adjusted.

4) Classification of Stages
The futuristic results achieved are based on the following:
The futuristic results achieved are based on the following:

1. Segmentation of skin lesion
2. Classification of skin lesion

The impact of decrease in the size of the skin lesion on the accuracy of classifiers is assessed.
Semi-supervised learning for CNN (Algorithm) model towards the identification of Skin melanoma and its stages 1, 2. .., n

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V. RESULTS

5.1 Dataset description

The dataset obtained from https://www.uco.es/grupos/ayrna/ieeet-mi (Sáez et al., 2016) comprises 81 attributes or features and is categorized into binary and multiclass segments.

Inside this dataset, there exist a total of 250 images depicting melanoma cancer. Among these, 29 melanomas have a size exceeding 1.5 mm, 54 fall within the range of 0.76 to 1.5 mm, and 167 have a size less than 0.76 mm. The features extracted from these photos, totalling 81 in number, have been employed for examination and modeling.

5.2 Evaluation indicators

Performance parameters are:

Accuracy = $\frac{(TP+TN)}{(TP+TN+FN+FP)}$

Sensitivity = True Positive Rate

Specificity = True Negative Rate

Precision = $\frac{TP}{(TP+FP)}$

Recall = $\frac{TP}{(TP+FN)}$

F1 Score = $\frac{2*(Recall*Precision)}{(Recall+Precision)}$

Mean Squared Error (MSE) MSE $= \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$

Where n is number of training dataset.

i represents ith training dataset.

is actual class.

$\hat{Y}_i$ is predicted class.

VI. CONCLUSION

The proposed approach of categorizing the skin diseases included the following groups which are benign, malignant and normal. The accuracy that the convolutional neural network obtained for the obtained data set was high at 94% compared to the SVM classifier that had a 86%. 6% accuracy. In the the traditional approach of developing an AI system to diagnose skin diseases, this method came up with deep learning based approaches to feature extraction. Compared to these previous works, the suggested marked enhancement offered a better accuracy and lower error rate in the objective AI systems. In the analysis, we provided a comparison of the constructed CNN architecture with other CNN models such as Alexnet, LeNet, and VGG 16 to detect skin cancer symptoms.

Following a similar training and testing process across the four distinct and well-known CNN models on the same ISIC data set and assessment of model accuracy and loss, the newly developed CNN architecture arrived at comparatively superior levels of accuracy and loss wherein the newly developed CNN achieved an accuracy of 94% and a loss of 17% when exposed to the same input. Out of all the aforementioned models, specifically the best test results: the CNN model was selected as the dermatology test due to its highest accuracy in different experiments. Thus, the proposed CNN model can be further introduced in the web and mobile applications for the diagnostics of skin diseases. These two approaches give results that are faster, more accurate and easier to use than the traditional methods especially for those who do not have a dermatological background. Other uncompleted ideas include fine-tuning the application to enhance the user's experience, tackling problems like batch size and time to test the model reaction to these factors in later studies, as well as using big data datasets to feed models in future research.

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