Improving Skin Cancer Diagnosis with Deep Learning: A Comparative Analysis of MLP and CNN Models"

Dheeraj Gupta, Shubham Sharma, Asif Mumtaz, Rajat Kumar Tiwari, Hamid Iqbal

Abstract: Skin cancer affects roughly around 2-3 million people, out of which 10-20% cases result in death. So, prevention and detection of skin cancer in early stages is vital and important. Melanoma skin cancer is generally more frequent, and this results in more deaths than any other type of skin cancer. Although, in biological field there are many procedures of detection, but rapid and accurate methods of diagnosis are required. The technique of image segmentation and diagnosis has become dynamic research forums in the field of computer vision under Deep Learning. Their utilizations are particularly developed into a well-known methodology in Medical Image Processing. Cancer is a kind of disease which develop into stages and to minimize the severity of cancer it is important to correctly diagnose the disease into early stages. Accurate assessments methods at the early stages of illness are intensively required to handle the cases which can mimic human brain and take decisions on behalf of human with far better accuracy. This research focuses on the development of rapid point-of-care diagnostics using convolution neural network (CNN) for diagnosing Melanoma at an early stage. This paper aims to bring out the fact that medical experts, especially dermatologist can efficiently and automatically classify melanoma patient from the normal ones by using deep learning algorithms more accurately. This study uses convolution neural network to analyze International Skin Imaging Collaboration (ISIC) archives and Human against machine (HAM) 100000 dataset collected from varied sources, images of previously diagnosed melanoma patient and normal mole and the observation says that the proposed CNN model achieves 98% accuracy by optimizing and tuning the parameters. The claims have been validated by showing comparisons between various machine learning classifiers using visualization tools.

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Keywords: Deep Learning, Skin Cancer, Convolutional neural network, Melanoma, Feature Extraction

1. Introduction

Skin cancers are the types of cancer which affect the outer and inner layers of skin. They are generally caused due to a long exposure to the harmful ultraviolet radiations of the sun. Skin cancer may affect one part of the body but due to the abnormal increase in the affected cells, disseminate to other tissues as well. Depletion of ozone layer is one of the reasons for rapid increase of skin cancer abnormal increase in the affected cells, which again gets distributed to different other organs. Depletion of ozone layer is one of the reasons for rapid increase of skin cancer Skin cancer is generally categorized as non-melanoma and melanoma cancer types. The latter one is more severe and dangerous compared to the melanoma. Non-melanoma skin cancer is around 80% of the total case of skin cancer. The categories under this category are identified as basal cell skin cancer and squalors cell skin cancer. This type of skin cancer may not result in death. If not detected on time, the demise cannot be replenished. Melanoma skin cancer begins with an irregular patchy surface over the skin and spread to other areas of the skin. This type of skin cancer results in death if not treated and cured at early stage.

The most common image classification algorithm under deep learning, which has given the highest performance in accuracy is Convolution Neural Network (CNN) developed by Zhou et al. [1] and his team. They have developed an algorithm based on deep learning and many datasets have been used to get the accuracy of the algorithm more fluent. In this research work we build an image classification model using deep learning and review the accuracy of CNN model. The CNN algorithm is not the first algorithm which is used for solving the problem of skin cancer, previously time and again many researchers used many algorithms to solve this problem with different approaches. Many of these researchers used other supervised and unsupervised machine learning algorithms like Support Vector Machine (SVM), Decision Trees (DT) and K-Nearest Neighbor (K-NN) but they the results are not that convincing as validated in deep learning algorithms. Deep learning model performance is directly proportional to the dataset. It increases with good amount of dataset as automatic feature learning is done in deep learning models but this is not applicable to machine learning model. The performance curve of machine learning model will be flattened after achieving a certain stage. This research work will try to achieve higher accuracy, and this is the one advantage of this research over other research for solving a problem which can be life threatening if the concerned patient does not get proper treatment. Since skin cancer is deadly and it can be very dangerous if not detected prior. The input is in the form of different images of patients taken from ISIC archives and other standard datasets taken from authentic sources.

The data set is selected purely based on severity of the skin cancer i.e. skin cancer has a variety of types and only a handful of them are very fast spreading dangerous and can cause death of a person. Write one line on novelty .

The main objective of this research is to solve the problem of automatic diagnosing melanoma skin cancer and normal mole in affected skin cancer patients using a deep learning algorithm called CNN and compare that CNN model with all other machine learning and deep learning models which are already discussed by other researchers. In order to come up with an efficient research on how to detect skin cancer using CNN we need to study the basis causes and the physical appearance and signs that lead the doctors to believe that the skin is infected with cancer. There was a need to study the biological process that happens in the skin when it gets infected. Moreover, in order to create a database, it was necessary to train the model with images of skin that is being infected with cancer. The main idea behind this is to make the machine smart enough to take its decisions by consulting the database as the referential and study material.

2. Background

Going back to the decade time, it has been observed that the cases of this disease has expeditiously increased to 53% [2]. The reason for the unfrequented growth is not entirely as a result of extended ultra violet (UV) introduction [3]. Regardless of the way that melanoma is one of the most destructive form of skin harmful development, a brisk determination can incite a high rate of perseverance.

According to the dermatologist, an underlying stage in finding the root cause of this disease lies in the visual evaluation of the questionable skin zone. An investigation is critical mainly due to the resemblances of few irritated sorts; in addition, the demonstrative exactness relates solidly with the master understanding of the specialist [4]. Without extra particular assistance given by dermatologists, the infected cases using visualization have reported an accurate figure of 65%-80% in melanoma end [5]. In estimated cases, the visual appraisal is with pictures (dermatoscopic) controlled and clicked by a phenomenal significant standard and enhancing clicking tool basically the high definition camera. The lightning is handled by using a channel to reduce reflections on the skin during recording to keenly observe the internal skin layers visible. This type of remedial assistances and duly perfectionist tools can help in getting closer to accurate skin sore examination which is almost about 49% more increased [6]. It can be further concluded by dermatologists that the blend of visual evaluation and dermatoscopic pictures [7] can help in giving both the internal and external view of melanoma disclosure precision of about 75%-84% [8].

2.1 Types of Skin Cancer cells

In general, the categories of namely four types in skin cancer are reported as basal cell, melanoma, seborrhea and psovarsid. The study of the categories is described below:

Basal cell skin cancer

In this type of skin cancer, there is a center raised area with blood vessels around it. This can be found around the areas of neck, shoulder and head. The skin affected area may also lead to bleeding if not treated properly.

Squamous cell skin cancer

It is present in the form of red scaly patch which is thickened due to long exposures to the ultraviolet radiations of the sun. User Interface creation and bleeding may occur in this type if left untreated, it may result into the formation of a large mass like structure.

Melanoma skin cancer

It is present in the form of red or black mole which is irregular in shape and size and can affect other tissues and structures in the body, if left untreated. The color of the skin in the affected area is discolored

2.2 Motivation and Contribution

In bioinformatics, research has demonstrated that pictures can be taken an important tool for man-made reasoning. Many explorations have been distributed with respect to the recognition of skin malignancy in beginning periods. Malignant growth is one of such infection which ought to be identified and restored in the earlier stages, else it would spread to varied tissues in the body which would eventually lead to the death of an individual. With the increase in advancement of technology, many procedures and diagnostic methods have been developed from time to time. But it is the need of the hour to integrate human knowledge into artificial intelligence that would extend human intelligence. The reason behind this study is to find an efficient solution that will help the medical practitioners to automatically classify the diseased in short span of time using computer assisted approach. The machine learning classifiers have been extensively used in the past and have shown tremendous approach in helping as a tool in hospitals, but with the advancement of technology, still gaps remain in identifying with greater accuracy and no compromise in results with medical fields. Therefore, deep learning algorithms, mainly CNN works well with images for binary classification. This research outlines the background of skin cancer and present the related review of diagnosing the disease using medical imaging techniques. It studies the previous state of art algorithms used for classifying the skin malignant growth problems using artificial intelligence (machine learning and deep learning algorithms). The existing gaps in the literature has been identified. Looking at the previous limitations, the novel approach of handling the melanoma cases has been identified and the detailed structure of the model has been proposed using CNN with measurable examination between pictures of melanoma and ordinary mole utilizing perception tools. The study lists the detailed accuracy of the model showing the training and validation loss. The performance of the machine learning classifiers with the proposed approach has been claimed with proper graphs and tables using visualization tools.

2.3 Related Work

There are a lot of research involved for practicing computer assisted systems in the domain of healthcare. Those researches include almost all the areas of medicine and obtain efficacious results especially when dealing with the images that are produced in the domain of medicine. For this purpose, many researchers previously attempt to solve this problem using machine learning algorithm, but the performance of their model is not quite satisfactory for experts. Machine learning algorithms are primarily classified as supervised, unsupervised and reinforcement machine learning algorithm. Reinforcement algorithm is now a topic of research where multiple researchers performing their research on this. Some researchers attempt to solve this problem of skin cancer using supervised machine learning algorithm and some researchers go for unsupervised learning to solve the problem of automatic diagnosing melanoma skin cancer. Supervised algorithm is used where labeled data is used for training the model whereas unsupervised learning algorithms are used where unlabeled data is used for training the model. In this exploration, analyst endeavor to take care of issue of diagnosing melanoma skin malignant growth utilizing regulated artificial intelligence [8] calculation like Support Vector Machine (SVM), K-Nearest Neighbor(K-NN), Decision tree (DT) where precision of SVM model is 89.5% , exactness of K-NN model is 82% , precision of DT model is 90 % graphically as appeared in Fig 1 .

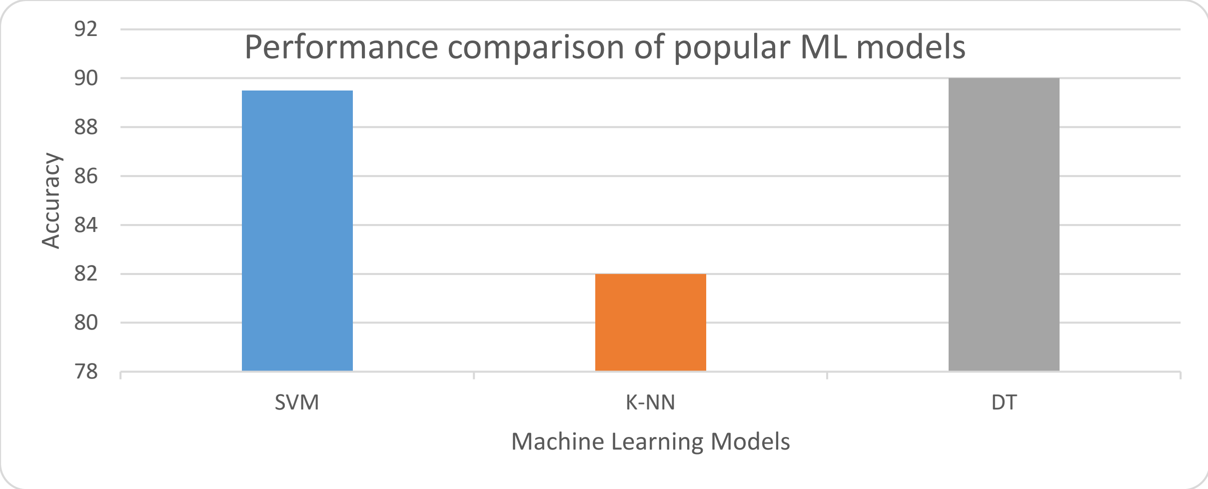

Fig 1: Accuracy of supervised machine learning model

In a similar exploration [9] specialist additionally endeavor to take care of the issue utilizing a profound learning calculation called Artificial Neural Network (ANN). ANNs are numerical frameworks comprising of many procedure units (neurons) associated with one another in a weighted way. The procedure unit gets signals from different neurons; joins, changes them and creates a numerical outcome. As a rule, the procedure units are relating generally to the genuine neurons and are interconnected in a system, with the goal that this structure comprises the counterfeit neural systems. Accuracy of ANN algorithm 92.5% this show deep learning model show better performance as compare to machine learning model, as appeared in Fig 2.

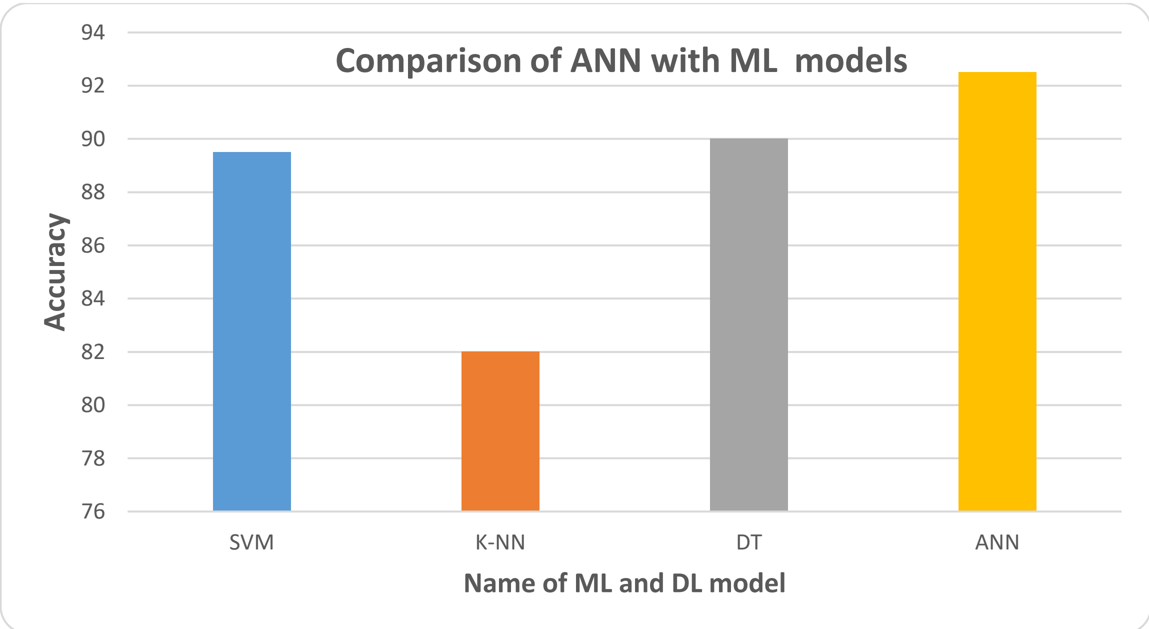

Fig 2: Accuracy of models

In the examination [10] analyst first, data advancement and data preprocessing were executed. As such, a formerly prepared Alex Net was utilized for the extraction of illustrative highlights. K-nearest neighbor (KNN) classifier utilizing cosine segment estimations to order the sores.

This was not endeavored in a free test dataset; just a cross-support was performed. The estimation accomplished an affectability of 92.1%, a manner of 95.18%, and an exactness of 93.64%. In spite of the unavailable self-administering test dataset, it is in like way fundamental to see that the region of vitality for each skin sore must be really clarified. An Alex Net model for incorporate extraction was similarly applied by Codella et al [11]. The authors, Gutman et al., [12] collected the dataset from International Skin Imaging Collaboration (ISIC) database with 2624 pictures based on dermatoscopy for detecting the cases from melanoma from non-melanoma versus atypical nevi. Despite the modified Alex Net yields, the makers in like manner used low-level carefully assembled features and features from insufficient coding, a significant residual framework, and a convolution U-compose. The performance was evaluated on vector machine. The makers definite a precision of 93.1%, an affectability of 94.9%, and and expresses accuracy of 92.8% for portraying melanoma versus no melanoma. In the more inconvenient partition among melanomas and atypical nevi, a precision of 73.9%, an affectability of 73.8%, and an accuracy of 74.3% were represented. The makers in like manner showed that the usage of significant features achieves an unrivaled display diverged that solitary used carefully assembled features.

Esteva et al [13] presented an achievement dispersion. The CNN model was applied on 129,450 pictures as input dataset images, out of which, 3374 found from dermatoscopic devices and addressed 2032 unmistakable covering (skin) wounds. Two twofold request issues were thought of: keratinocyte carcinomas versus charitable seborrheic keratosis and undermining melanomas versus liberal nevi. The authors used an inception V3 model from GoogLeNet for the portrayal, which was pre trained with the tremendous picture database ImageNet. The parameters were optimized and tuned to get the best performance results. A remarkable property of this philosophy is the usage of a novel tree-composed disease logical arrangement in which the individual sicknesses structure the leaves of the tree. The inward center points bundle together individual afflictions that are ostensibly and clinically comparable [29]. To choose the probabilities of a coarser physical issue class (i.e., an inside center point at a progressively raised level in the tree), the probabilities of the child centers of this coarser sore class are included. This proves the efficiency and accuracy of CNN models. The CNN model was attempted with test data that were totally biopsy-fixed and achieved a receiver operating characteristic curve (ROC) area under curve (AUC) of .96 for carcinomas, a ROC AUC of .96 for melanomas, and a ROC AUC of .94 for melanomas organized uniquely with dermatoscopic pictures.

An Alex Net model for highlight extraction was likewise applied by Codella et al [11]. Rather than Gutman et al [14], in any case, an aggregate of 2624 dermatoscopic pictures from the openly accessible International Skin Imaging Collaboration (ISIC) database were utilized for the arrangement of melanoma versus nonmelanoma sores or melanoma versus atypical nevi.

Notwithstanding the adjusted Alex Net yields, the creators additionally utilized low-level high-quality highlights and highlights from scanty coding, a profound leftover system, and a convolution U-arrange. Characterization dependent on these highlights was then performed utilizing a help vector machine. The creators revealed an exactness of 93.1%, an affectability of 94.9%, and an explicitness of 92.8% for ordering melanoma versus nonmelanoma. In the more troublesome separation among melanomas and atypical nevi, a precision of 73.9%, an affectability of 73.8%, and a particularity of 74.3% were accounted for. The creators additionally indicated that the utilization of profound highlights brings about a superior presentation contrasted with classifiers that solitary utilized low-level carefully assembled highlights.

Han et al [15] are particularly basic for their reliable straightforwardness since they have made their PC computation uninhibitedly available for outside testing. The gathering introduced a classifier for 12 arranged skin illnesses reliant on clinical pictures. They built up a Residual Neural Network (ResNet) model that was aligned with 19,398 getting ready pictures. With the straightforwardly open Asan dataset, the CNN model achieved ROC AUCs for the finishes of melanoma, basal cell carcinoma, squamous cell carcinoma, intraepithelial and carcinoma of .96, .96, .83, .82, and .82, solely.

An outfit of CNNs for the portrayal of melanomas versus nevi or lentigines is introduced by Marchetti et al [16]. They executed five systems to consolidate each robotized conjecture from the 25 taking an intrigue bunches in the International Symposium on Biomedical Imaging (ISBI) 2016 Challenge into a single plan result. Therefore, they endeavored two non-learning approaches and three Artificial Intelligence (AI) techniques. The blend computations were set up with 279 dermatoscopic pictures from the ISBI 2016 Challenge dataset and were endeavored with 100 other dermatoscopic pictures from the equal dataset. Considering ordinary precision, energetic blend was the best-performing troupe method with an affectability of 58% and an identity of 88%.

The as of late introduced two-advance approach by Bi et al [17] in like manner falls under the grouping "picking up without any planning" in light of the methodology for getting ready of the ResNet model for the three-class portrayal of melanoma versus seborrheic keratosis versus nevus. Bi et al [17] used approximately 3600 dermatoscopic pictures from the ISBI 2017 Challenge dataset and additional photos from the ISIC Archive to achieve the results uncovered.

In Nasr-Esfahani et al [18], a dual layer Convolution Neural Network (CNN) was set up without any planning as capability of melanoma versus liberal nevi subject to clinical pictures. Only 136 pictures were used to set up the model and the test dataset contained only 34 pictures. The photos were all from the open picture narrative of the Department of Dermatology of the University Medical Center Groningen. This strategy accomplished an affectability of 81%, a particularity of 80%, and an exactness of 81%. In any case, the outcome ought to be seen basically in light of the fact that the test dataset was restricted.

Mention the research gaps.

3. Proposed Work

In this research, deep learning come into picture because machine learning is not well suited for large amount of data which means as the amount of data increases machine learning perform well to a certain stage after that there will be no significant effect on the performance of a model with increase in amount of data. CNNs are neural systems with a particular engineering that have been demonstrated to be extremely incredible in regions, for example, picture acknowledgment and characterization [19]. CNN has shown the ability to distinguish facial features, articles, and traffic signals superior to people thereby can be useful in implementing the artificial intelligence and machine-controlled vehicles. The fundamental necessity for the fruitful preparing of profound CNN models is that adequate preparing information marked alongside the classes are accessible. Something different, there is a danger of overfitting the neural framework and, thus, an insufficient hypothesis property of the framework for dark data. There is an exceptionally restricted measure of information openly accessible for the order of skin injuries. Practically completely distributed techniques use datasets that contain far under 1000 preparing information focuses per instructional course. In correlation, notable CNN models for picture characterization, for example, Alex Net [20], VGG [21], GoogLeNet [22], or ReSNet [23], are prepared by means of the enormous picture database ImageNet and have more than 1000 preparing pictures for each instructional course.

For this research work dataset will be curated with certain number of images of the patients affected from the skin cancer into a dataset. Dataset should contain a fairly good number of images so that our algorithm would be trained to abstract better and accurate information and is able to distinguish between healthy skin and skin affected by cancer. Convolution Neural Network (CNN) is the most well-known profound learning calculation [25] which we use for our examination work.

For instance: - The input is taken in the form of red green blue (RGB) components and fall under the information grid as pictures. Each picture goes past convolutional and pooling layers and a component map was acquired by utilizing straight and non-direct capacity the information grid. After that a concealed layer is utilized which works in the comparable design as the neurons that is accepting and transmitting signals lastly yield layer is created which is the outcome.

3.1 Model Used

Data work as a fuel for a machine learning and deep learning models. The primary important task is collection of external sources of information. CNN is the widely used model for classifying the disease from normal and melanoma (Fig 3). The bulk data collected has to undergone to cleaning and preprocessing is necessary after data extraction. The dataset is converted into useful information by preparing it into relevant and useful data, which is then stored into database that would ultimately be used as training image of the model. Then dataset is divided into training image dataset and test image dataset in ratio 3:1 and using training image we trained a model and when any random skin image of a person as input to the model it is able to classify whether the person is infected with melanoma or not.

The classifier invoke the predict () function into a variable and if the value of variable is zero the condition is called melanoma and if non zero value is encountered then the birth mole is evoked and the text image dataset preprocess the image and extract the features of the image to generate user demanded results.

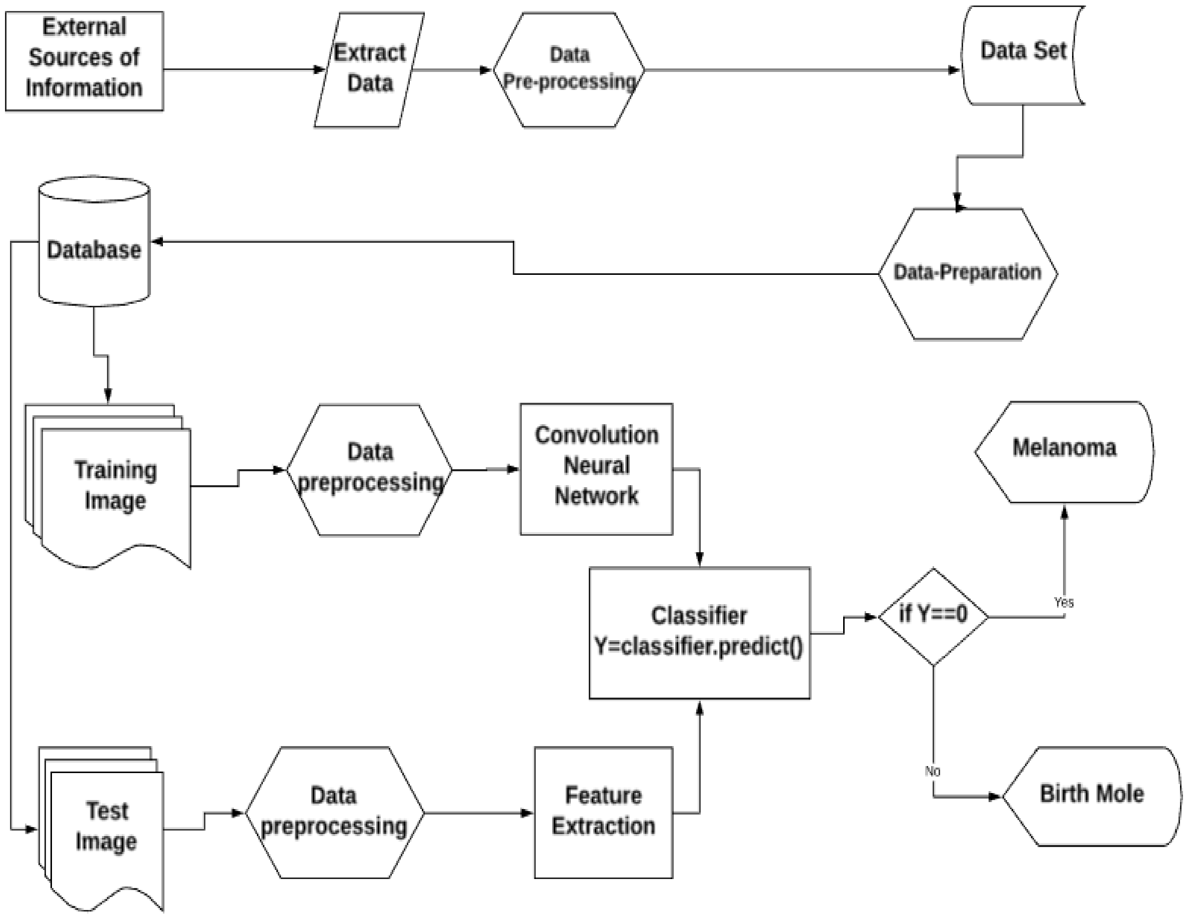

Fig 3: Overall Structure used in the paper

This work shows statistically the comparison between image of melanoma and normal mole using histogram. Histogram is one of the ways to represent the approximation of distribution of categorical and numerical data. Histogram of melanoma is shown in Fig 4 and histogram of normal mole is shown in Fig 5. The two figures show the comparison between melanoma and normal Mole.

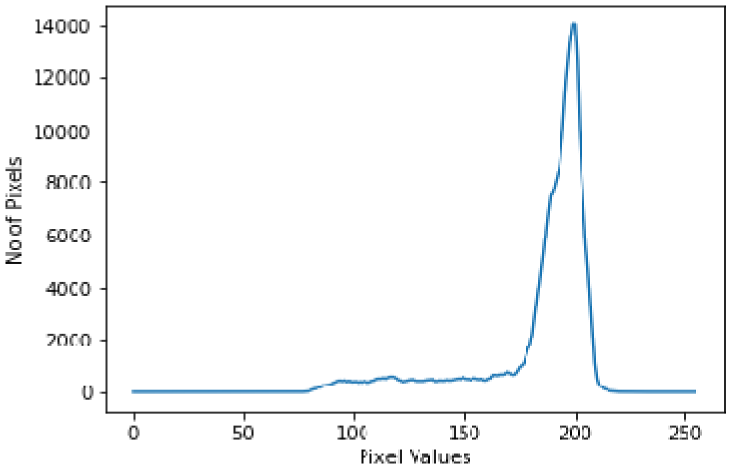

Fig 4: Histogram of Melanoma

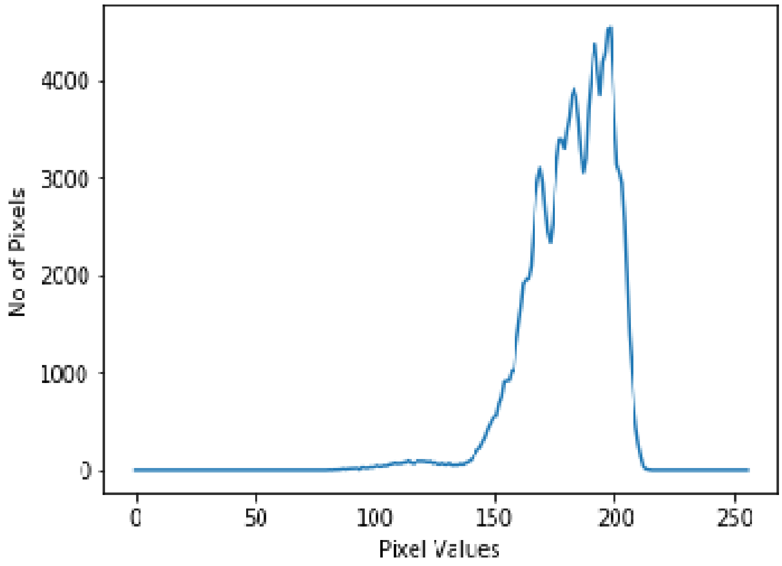

Fig 5: Histogram of Normal Mole

4. Results and Discussions

For this research work, the dataset is created by collecting several images of melanoma skin cancer and normal mole. The source of melanoma images is ISIC archives and HAM100000 dataset whereas the dataset of normal mole is curated by collecting images of a normal mole from sources like Google images and Microsoft Bing. Once the complete dataset is curated from all external sources. Pictures are part in the proportion 3:1 which mean around 75% of absolute pictures are utilized for preparing the model and 25% of all out pictures are utilized to approve the model to check whether the model is working fine for another info or not. On this basis, the accuracy of the trained model which is a metric use to measure the performance of the model is achieved. When this model is trained using CNN, training image dataset [26] has to pass through different layers of CNN and every layer has some specific operations and the result of these operations is shown in fig 4. Since CNN is a deep learning algorithm which means it contain more than one hidden layer and all these layers are helping for building a best deep learning model [27] to detect the infected skin cancer disease. The Fig 6 shows the details of the parameters used for optimization and tuning the parameters in the proposed model.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_4 (Conv2D)            (None, 62, 62, 32)        896
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 31, 31, 32)        0
_________________________________________________________________
dropout_4 (Dropout)          (None, 31, 31, 32)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 29, 29, 32)        9248
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 14, 14, 32)        0
_________________________________________________________________
dropout_5 (Dropout)          (None, 14, 14, 32)        0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 12, 12, 32)        9248
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 6, 6, 32)          0
_________________________________________________________________
dropout_6 (Dropout)          (None, 6, 6, 32)          0
_________________________________________________________________
flatten_2 (Flatten)          (None, 1152)              0
_________________________________________________________________
dense_3 (Dense)              (None, 128)               147584
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 129
=================================================================
Total params: 167,105
Trainable params: 167,105
Non-trainable params: 0
```

Fig 6: Convolution Layers

While building an image classification model using CNN algorithm, the image has to pass through different layers and the first layer of CNN is convolution and this layer will generate a feature map from an image using a kernel which is also popularly known as feature detector. Original Image is shown in Fig. 7, feature detector is shown in Fig 8 and using this a Feature map [28] is generated which is shown in Fig 9. As there are three significant things to refer to in this procedure: the original picture, feature detector and feature map. The original picture is the picture being recognized. The feature detector is a network, typically 3x3 (it could likewise be 7x7). An element identifier is likewise alluded to as a piece or a channel.

Original Picture * Feature Detector = Feature Map
6 X 6 (Convolution Operation) 3 X 3 4 X 4
(n) (f)

size of feature Map= n-f+1
=6-3+1
=4

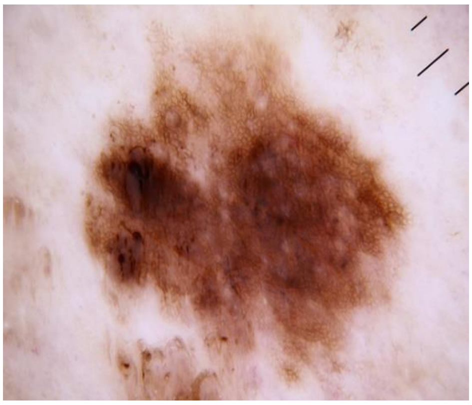

Fig 7: Original Image of melanoma

1	1	1
1	1	1
1	1	1

Fig 8: Feature Detector

Feature Map is generated in Convolution layer after a Convolution operation is shown in Fig 9.

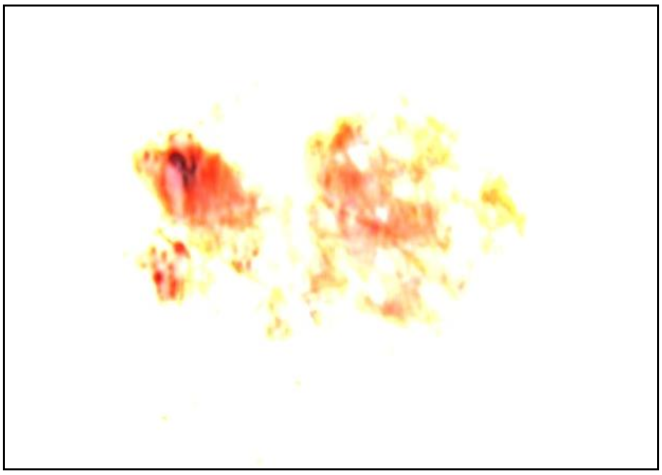

Fig 9: Feature Map of Melanoma

The model is trained using training image dataset this dataset consists of 1392 images of melanoma and 1392 image of normal mole. Using training image dataset, a classifier is trained, and validation of the model is done by passing a random image through the model to check whether the model is working fine or not. Implementation of the proposed work as appeared in Fig 10.

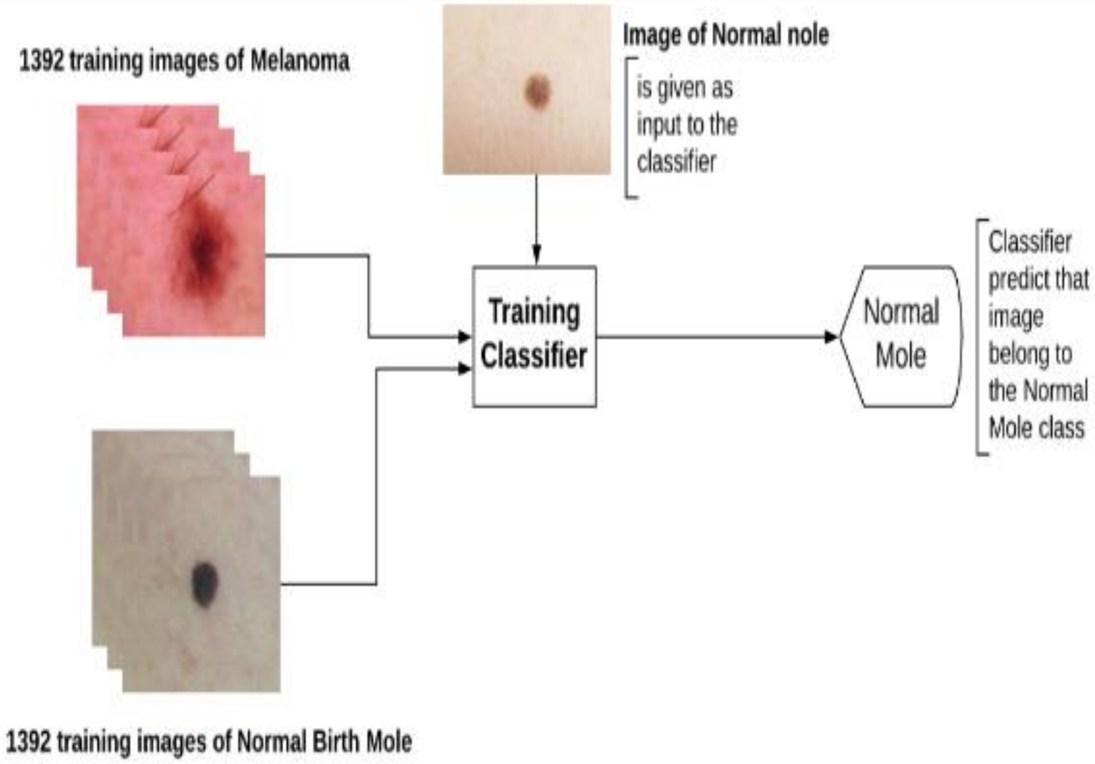

Fig 10: Overview of Implementation give high quality

The model is trained with the help of training s/et based on training image dataset and validation is used to evaluate the performance of model. The parameters are set for 10 epochs. The graph between training and validation accuracy is shown in Fig 11 and the graph between training and validation loss as appeared in Fig 12.

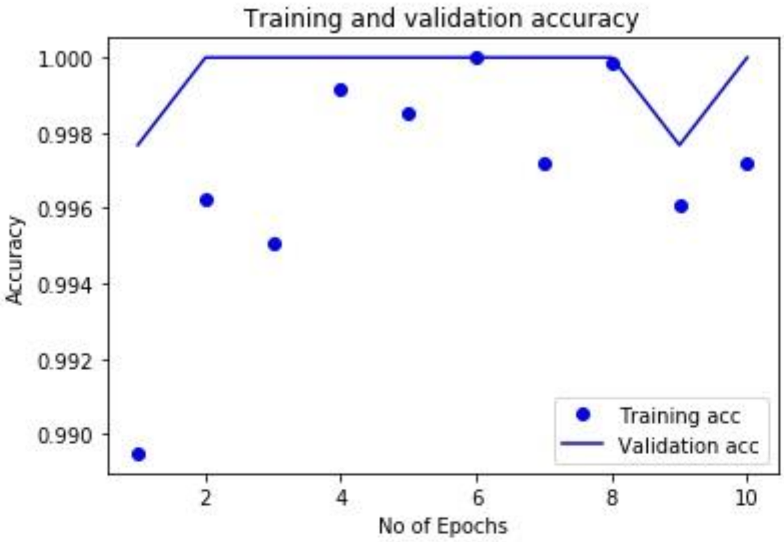

Fig 11: Training and Validation Accuracy

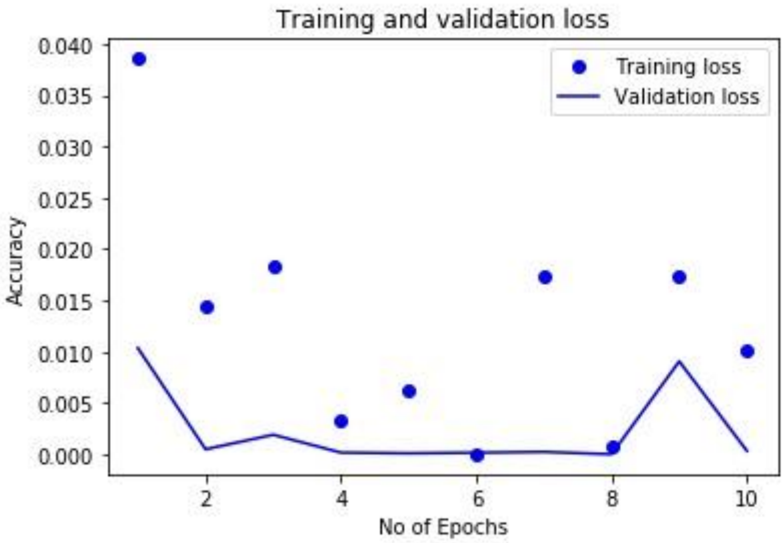

Fig 12: Training and Validation loss

The accuracy of around 98% accuracy is achieved with the proposed model. Fig 13 graphically shows the importance of using deep learning algorithm specially CNN algorithm over other machine learning algorithm for diagnosing melanoma in affected skin cancer patients.

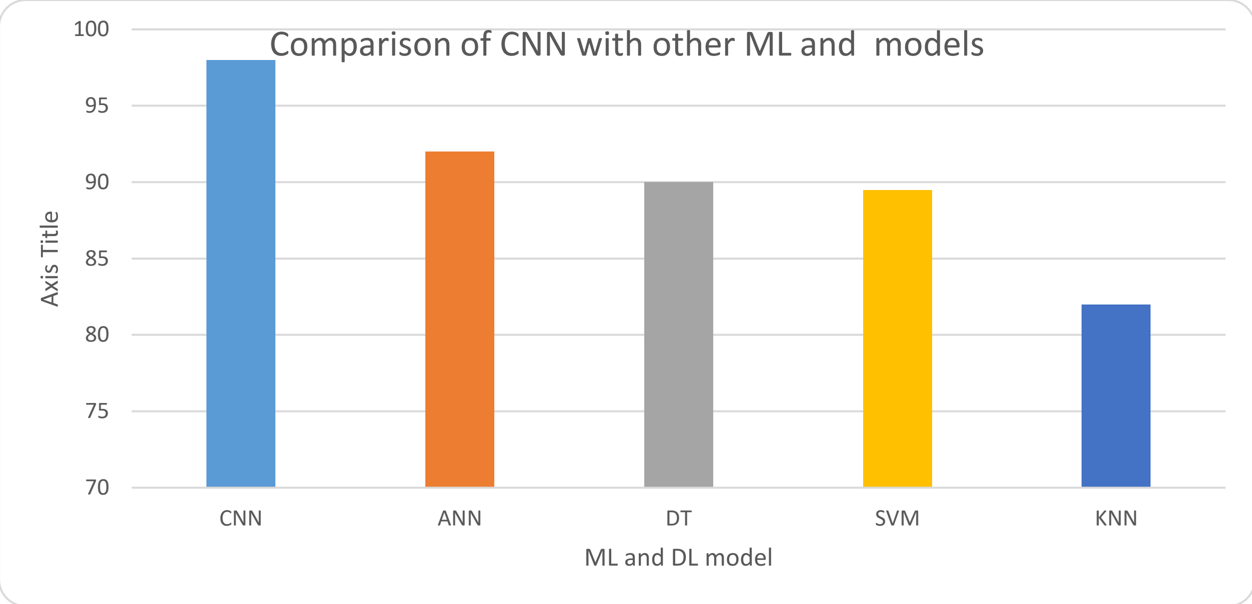

Fig 13: Comparison between accuracy of Deep learning and machine learning algorithm

5. Conclusions

This paper prioritizes to automatically diagnose melanoma skin cancer and normal mole in affected skin cancer patients using deep learning algorithm. The work validated the experimental results by optimizing tuning the parameters used in CNN for receiving its superior performance and its effectiveness than other traditional state of art approaches. The features are automatically erudite by the proposed CNN model which is used to perform classification tasks accurately and effectively. This research will help in saving more lives and it ease the work of dermatologist. By using this implementation dermatologist can give more time to patients who are diagnosed with skin cancer instead of wasting time on patient which are not infected by skin cancer disease like melanoma. The performance of the proposed model has been validated with the accuracy results received with the testing set of datasets using image classification method. The future of this research work can be extended to dealing with bigger datasets using a deeper CNN for better results.
Add future scope

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