Design thinking approach for Melanoma Skin Cancer Detection using a Hybrid Deep Learning Neural Network

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Abstract—The design thinking approach for melanoma has increased over the past three decades, but the fatality rate from this kind of skin cancer has decreased because to advances in diagnostic methods. Hence, an automated, trustworthy system that can identify the existence of melanoma via a dermatoscopic picture of skin pigmentation might be an extremely important instrument in the field of medical diagnostics. In the event that this kind of skin cancer is not caught in its earliest stages, it has the potential to metastasize (spread to other regions of the body). Hence, the adoption of automated diagnosis systems has led to significant progress in the medical industry, since they aid both professionals and laypeople in identifying certain diseases. This paper introduces a novel hybrid model for identifying Melanoma skin cancer by combining XGBoost classifier with Deep Learning Neural network. Using the NodeMCU IoT Module, the trained model's classification result is communicated to the OLED Display. The HAM10000 Dataset was used for all stages of the proposed model's development cycle, from training to validation to testing. The suggested model improves upon the highest accuracy on the test dataset while maintaining a reasonable degree of accuracy overall. The findings obtained using the suggested model indicate a substantial enhancement over the findings acquired using the state of the art when it comes to the effectiveness of skin lesion classifiers.

***Keywords*—Deep Learning Neural Network, XGBoost Classifier, Skin Cancer, Melanoma, design thinking, empathize, ideate, prototype.**

I. INTRODUCTION

Despite the fact that it makes up 4% of all skin cancers, melanoma is responsible for 75% of all skin cancer fatalities. Early detection and treatment of melanoma increases the likelihood of a successful outcome; but, if detected at a later stage, the cancer may have already invaded deeper layers of skin or migrated to other organs [1]. In addition to being difficult to cure, its spread beyond the skin can be dangerous. Melanocytes are responsible for Melanoma's spread to all organs. Melanoma is typically brought on by years of prolonged exposure to the sun's UV rays. Through the combination of incident light and oil immersion, dermoscopy provides a visual examination of the skin's constituent parts without causing any harm to the patient. Melanoma is more likely to be detected using dermoscopy than with unassisted observation, however the diagnostic accuracy of this method is highly dependent on the dermatologist's level of expertise [2]. Melanoma is difficult to distinguish from melanocytic nevi, especially in its early stages. This highlights the need of an automated diagnosis tool for doctors. Melanoma may be diagnosed with an accuracy of 75-84% even when performed by skilled dermatologists using dermoscopy. Computer aided diagnosis can improve both the speed and accuracy of diagnoses. Although while computers aren't smarter than humans, they may sometimes pick up on subtleties that our eyes miss, such as subtle differences in colour or texture. Prevalence of melanoma is higher in males than in women, and among people with pale skin and extensive exposure to sunlight (whether from the sun or tanning beds) [3]. The white population is seeing a higher rate of newly diagnosed illnesses than any other racial or ethnic group. Based on age-adjusted cases diagnosed between 2015 and 2019, the annual rate of new cases of cutaneous melanoma was 21.5% per 100,000 men and women. In 2010, there were 21.5 new instances of melanoma of the skin for per 100,000 men and women. There were 2.1 deaths per every 100,000 people per year. Using data from 2015-2019 diagnoses and 2016-2020 fatalities, these rates have been corrected for age [7]. Figure 1 shows the past 5 years new cases and death of Melanoma.

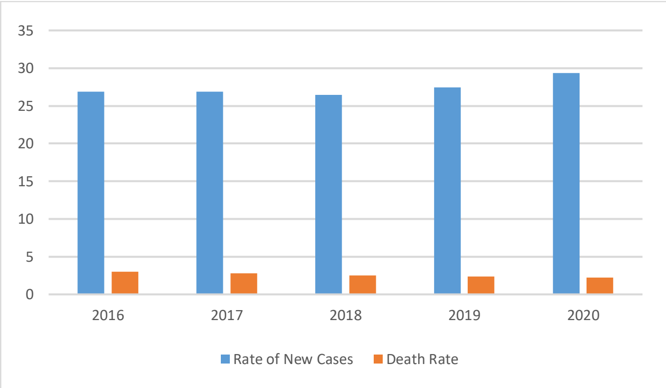


Figure 1 : Past 5 Years New Cases/Death of Melanoma Skin Cancer

In today's world, cancer disorders are one of the most lethal health problems a person may face. Not catching melanoma skin cancer in its early stages can be fatal, making it one of the most lethal forms of the disease. Death rates from melanoma skin cancer are lowered and treatment-related problems are minimized when the disease is detected early [4]. A dermatologist makes a diagnosis after collecting a biopsy from the patient. The effectiveness of an examination is contingent on the skill and equipment of the examining physician.

In order to make a correct diagnosis of such disorders, medical professionals may require extensive training and precise methods. Dermatologists place a premium on having access to accurate tools because they improve diagnostic accuracy, enhance patient care, and reduce the amount of unnecessary biopsies. As a result, we've thought about how AI may play a part and how different AI approaches could be applied to the problem. AI techniques (and, especially, deep learning) can aid clinicians in making diagnoses as well as make the procedure simpler for patients when used to the diagnosis of such disorders [5]. It is evident from the foregoing that these methods can help doctors save time and energy while still allowing for a correct diagnosis.

For issues like these, where the clinician has to make quick, accurate decisions based on little information, deep learning has shown to be an effective tool.

A. *Melanoma Skin Cancer*

As melanocytes (the cells responsible for the skin's tan or brown hue) begin to multiply uncontrollably, melanoma develops. The onset of cancer occurs when unchecked cell growth in the body becomes the norm. Cancerous cells can form in virtually any organ or tissue in the body and metastasize to other organs or tissues.

As compared to other forms of skin cancer, melanomas are quite rare. Yet, melanoma poses a greater threat because to its metastasis-prone nature. Although while melanomas can appear anywhere on the skin, they most commonly manifest themselves on the trunk (chest and back) in males and the legs in women. Likewise, the neck and the face are frequent targets. Although while the chance of developing melanoma on the face, neck, arms, and legs is reduced in those with darker skin, anybody can get melanoma on the palms of their hands, the soles of their feet, or beneath their nails. Black Americans have a substantially higher rate of melanomas in these locations than whites.

B. *Symptoms of Melanoma*

Even in places that don't see much sunlight, such the palms of your hands, fingernail beds, and the bottoms of your feet, melanomas can develop. People of colour are disproportionately affected by these occult melanomas. A mole is not necessarily the first sign of melanoma. It's possible for it to manifest on skin that looks completely healthy otherwise.

Early melanoma symptoms often include:

- An evolution of an existing mole

- A change in skin pigmentation or the appearance of a new, suspicious mole

C. *Melanoma Risks*

Fair skin

If your skin doesn't have as much melanin (pigment), you won't be as protected from the sun's rays. Melanoma is more common in those with fair skin, blonde or red hair, blue or green eyes, and a propensity to freckle or burn easily. However persons of color, such as Hispanics and African-Americans, are at increased risk for developing melanoma.

A history of sunburn

A higher chance of developing melanoma is associated with having had one or more blistering sunburns.

Excessive ultraviolet (UV) light exposure

There is an increased chance of acquiring skin cancer, especially melanoma, after being exposed to ultraviolet (UV) radiation, whether it comes from the sun or artificial means such tanning lamps or booths.

Having many moles or unusual moles

If you have more than 50 ordinary moles, your chance of developing melanoma is significantly higher. Having a mole of an uncommon kind is also a risk factor for melanoma. These moles, which are called dysplastic nevi in the medical community, are bigger than average, have ragged edges and a mottled coloring.

A family history of melanoma

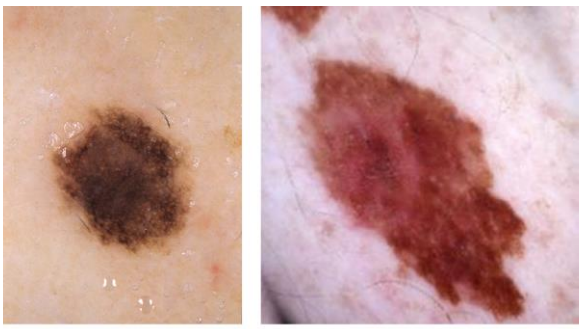
Your risk of acquiring melanoma is increased if a parent, child, or sibling of yours has been diagnosed with or died from the disease.

Weakened immune system

Those who already have a compromised immune system are more likely to develop melanoma or another skin cancer. Using immunosuppressant drugs after an organ transplant or having an immune-compromising illness like HIV/AIDS might weaken your body's ability to fight against infections.

D. *Dataset*

The research uses a dataset of Melanoma cases and diagnoses obtained from the Kaggle website [6]. Normalization was performed on the HAM10k dataset's dermoscopy pictures to ensure uniformity in terms of brightness, colour, resolution, etc. More than half of the cases had the true diagnosis confirmed by histology (also known as the source of truth), which is twice as many as in the previously published skin lesion datasets. Expert dermatologists came to a consensus on the diagnosis of the remaining lesions. Instead of attempting to categorise seven skin lesions in an unbalanced dataset, let's narrow our focus to determining whether or not they are Melanoma. Sample Normal and Melanoma photos from the dataset are graphically shown in Figure 2.



(a) Normal (b) Melanoma

Figure 2 :Dataset Sample Images

Here we demonstrate the computational deep learning method for differentiating melanoma skin cancer photos from those that do not include the disease. To create an effective network for identifying melanoma skin cancer, we utilized the python script TensorFlow, the Colaboratory, and deep learning architectures. Our goal was to educate a Hybrid model specifically for determining whether or not a picture contained melanoma. The major goal of this function is to identify shared features across the photos and assign them to a predetermined set. This work's summary sections provide an in-depth overview of the following details, such as Section-II, which concisely summarizes the relevant research, and Section-III, which does the same for the proposed approach approaches. In Section-IV, we go into further depth about the results and discussion sections, and in Section-V, we draw a conclusion and consider possible applications of the proposed method.

II. Related Study

The World Health Organization (WHO) ranks melanoma, a kind of skin cancer that may be passed from person to person, as the worst disease there is. Many different auto diagnostic procedures and instruments have been developed by researchers for the progressive identification and categorization of melanoma cancer. In the publication [8], the authors offer a new method of random feature coordination schema for detecting and classifying skin cancer. The approach makes use of a deep neural networking (DNN) architecture to classify and provide trustworthy decision help on processing data-types.

The amount of documented cases of skin cancer has already been steadily climbing for decades. Melanoma, basal cell carcinoma, and squamous cell carcinoma are the three most common forms of skin cancer. Melanoma is the most lethal kind of skin cancer, and it is only treatable if caught in its earliest stages. Melanoma is a cancer that is notoriously difficult to diagnose in its early stages. As a result, many tools have been created to aid in the detection and diagnosis of melanoma. Identifying characteristics of the disease are crucial in making a correct diagnosis. Finding the optimal blend of characteristics and machine learning strategies for categorization is also crucial. Using a digital picture dataset called MED-NODE, the researcher of [9] created a method to identify melanoma skin cancer. The raw photos in the dataset are contaminated with artefacts of varying types, necessitating the initial step of the procedure to be the application of preprocessing. After that, we apply Active Contour segmentation to isolate our target area. The system's effectiveness is evaluated using three classifiers, and several color characteristics were collected from the segmented portion. The system's Decision Tree accuracy is higher than that of competing classifiers at 82.35 percent.

Around five million people in the United States alone receive a new diagnosis each year. The most aggressive and potentially fatal form of skin cancer is melanoma. Melanoma has traditionally been diagnosed by a combination of a doctor's keen eyes and deft hands. This procedure is laborious and rife with potential for mistakes. Dermoscopy photos capture skin without surface reflection, allowing for clearer viewing of the skin's deeper layers. Notwithstanding these factors, a lesion picture includes a lot of artefacts, sounds, and a complicated structure. Image complexity means that detecting borders, extracting features, and classifying pictures is a challenging task. We need improved classification and prediction algorithms to categorise pictures so that early-stage melanoma can be identified and predicted. Thus, an effective, efficient, and precise melanoma identification, classification, and prediction system is required to enable its detection and categorization at an incredibly early stage. In paper [10], the author evaluated several different deep learning algorithms for classifying skin lesion images using the publicly available large data sets from the International Skin Imaging Collaboration (ISIC) archive. These algorithms included Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). In addition, the raw datasets from the ISIC will be preprocessed and scaled so that they may be used by algorithms. In addition, five metrics, including ROC, will be used to evaluate and compare the efficacy of these techniques.

Cancer of the skin affects people all over the world. Both children and adults are at risk for developing this condition. Melanoma is the most lethal and common kind. Melanocyte cells, which produce melanin, are affected, and the condition quickly spreads to other parts of the body. A lower death rate from melanoma can be achieved with earlier diagnosis. For traditional clinical approaches to work, dermatologists would have to examine each patient, which is time-consuming, expensive, and inconvenient. The use of automated detection aids in obtaining reliable findings. Melanoma feature extraction and selection from dermoscopy pictures is a difficult problem. By fusing the features of a Gray Level Co-occurrence matrix, a local binary pattern, as well as a pre-trained convolution neural network, the author of [11] hopes to extract effective features. The question of whether or not the combination of two strong traits results in improved performance has been the subject of experimentation. The PH2 and ISIC2017 databases were employed in the proposed system. Compared to either deep or handmade features alone, the experimental findings show that a combination of the two yields superior classification performance.

Melanoma is the most dangerous kind of skin lesion and skin cancer has become the most frequent type of cancer in recent years, especially in humans. Early cancer detection is crucial, but distinguishing between non-melanoma and melanoma requires the expertise of a board-certified dermatologist. The use of CADs for diagnosing skin cancer has received little research. In this study, we aim to develop a method for the automatic detection of Melanoma using digital image processing. In paper [12], a method is shown that uses dermoscopy lesion pictures to automatically apply the ABCD rule. First, we employ a pre-processing phase called hair removal, which makes use of a morphological filter and thresholding. Lesions are ultimately categorized as malignant (melanoma) or benign (benign).

III. SYSTEM METHODOLOGIES

The detection of Melanoma Skin Cancer makes use of both deep learning models and many traditional machine learning techniques. The primary goal of this work is to create a reliable model capable of identifying Melanoma Skin Cancer. In this piece, we propose the DLXG technique, a hybrid that combines the best features of Deep Learning neural networks (DLNNs) and XGBoost classifiers. We'll show you how this model is so precise and efficient that it changes the game. Image capture, picture pre-processing, feature extraction, classification, and accuracy estimations are the cornerstones of this approach to diagnosing Melanoma skin cancer.The suggested model's schematic diagram is seen in Figure 3.

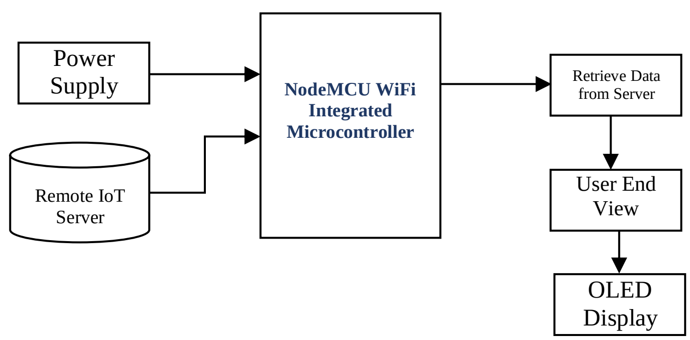


Figure 3 : Block diagram of Proposed Model

Data Collection

This is the beginning of the process that will ultimately help you achieve your study's goals. In order to begin processing a picture, one must first acquire it. The process entails rescuing the picture from its original location, which is typically some sort of hardware. Melanoma Skin Cancer Dataset was obtained from the Kaggle website, where photos are annotated as either Melanoma or Normal Images.

Data Preprocessing

To train the system, an input image is provided, which may be captured under any lighting scenario. That's why preparatory work is required. Resizing the image and adjusting the contrast and brightness are included in this case as part of the pre-processing. It's done like this to fix the image's uneven lighting. Images require picture preprocessing prior to their use in model training and inference. The dimensions, direction, and hue are not the only things it has. It is required to do preprocessing on image data before using it as input to a model. To get rid of hair in photos, we use blackHat filtering on a grayscale image to identify hair's edges. The inpainting process begins with a step in which the hair's shapes are emphasized in order to receive the necessary attention.

Extraction of Features

When a large amount of raw data needs to be broken down into more digestible chunks, a technique called "dimensionality reduction" might help: enter feature extraction. This will make processing simpler whenever you need it. The abundance of variables in these massive data sets is their defining feature. Having to deal with these variables takes a lot of processing power. The optimal feature may be extracted from these massive data sets using segmentation method by selecting and combining parameters into features. These properties can accurately represent the underlying data set, while also being simple to implement.

Classification

Classifiers and similar software are required for the training process because they take in large data sets, process and evaluate them, and then provide actionable features. The goal of this method is to assign each pixel in a digital picture to one of many predetermined categories. Multi-spectral data are typically utilized for this classification process, and the spectral pattern included in the data for each pixel serves as the quantitative foundation for the various categories. The purpose of image categorization is to determine the real-world objects depicted in a picture and assign each one a distinct shade of grey (or color). Maybe the most crucial aspect of digital image analysis is picture categorization. Image classification has been an essential challenge in the field of computer vision due to the difficulty of distinguishing among different types of objects for categorization. The term "image categorization" describes the process of assigning a label to a picture that fits into one of several categories. Exactly n categories exist into which each given image may be placed. It would be really helpful if we could automate the process of reviewing and classifying photographs using computer vision, as doing it manually may be a time-consuming effort, particularly when dealing with a large volume of images.

Deep Learning Neural Network

Layers of nodes make up artificial neural networks (ANNs) and are divided into the input layer, the hidden layers, and the output layer.In order to determine whether or not a node should be activated and its information forwarded to the following level of the network, its result is compared to a threshold. If that's the case, information won't be sent to the next network level. To learn and gradually increase their accuracy, neural networks must be exposed to training data. After these learning techniques have indeed been fine-tuned for accuracy, they represent powerful things in the disciplines of computer science and artificial intelligence, enabling us to swiftly classify and group information. When opposed to the hours it takes for human professionals to manually identify something, heavy tasks like speech recognition or picture recognition may be completed in a matter of minutes with the right technology.

The process through which deep learning-powered computers learn to recognize diseases is very similar to that experienced by the child. Each subsequent method in the

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hierarchy learns from its predecessor by applying a nonlinear change to the input. The result is a statistical model. Several iterations are performed until the output is reliable enough to be used. The term "deep" was used to describe the extensiveness of the processing stages that information must undergo.

XGBoost Classifier

One common supervised-learning technique for large-scale regression and classification tasks is XGBoost (eXtreme Gradient Boosting). Sequentially constructed shallow decision trees are used to produce precise outcomes and a training strategy that is extremely scalable while avoiding overfitting.

Similar to the random forest approach, Gradient Boosting Decision Trees (GBDT) is an ensemble learning method for categorization and regression based on decision trees. By combining various machine learning techniques, "ensemble learning" algorithms provide more accurate predictions.

Hybrid DLXG Model

In order to develop our DLXG model, we substituted out the Deep Learning Neural Network Model's final network output with an XGBoost classifier. For such output nodes of the last level of the DLNN network, these are once again the predicted probabilities for input sequences. Each output probability is derived using an active function. The question of whether or not a neuron should fire is resolved by an Activation Function. This implies it will use less complex mathematical procedures to determine whether or not the neuron's input to the network is relevant to the prediction process. For training a network, the Adam Deep Learning Optimizer technique uses an extension of stochastic gradient descent to adjust the weights of the nodes as necessary. Adam optimizer modifies the learning rate for each network weight independently, whereas SGD keeps a constant learning rate throughout training. Figure 4 depicts the steps involved in creating the new hybrid DLXG model.

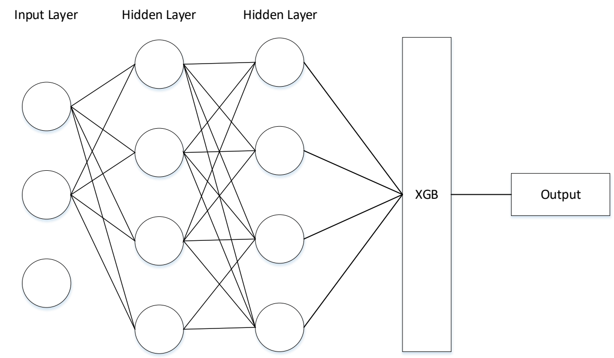

Figure 4 :Elements of the DLXG Process

NodeMCU IoT Module

NodeMCU is an affordable open-source IoT platform. At first, it was comprised of software designed to function with Espressif Systems' ESP8266 Wi-Fi system-on-a-chip (SoC) and hardware based on the ESP-12 module. The ESP32 32-bit MCU was added later with support. Figure 5 shows the NodeMCU IoT Module.

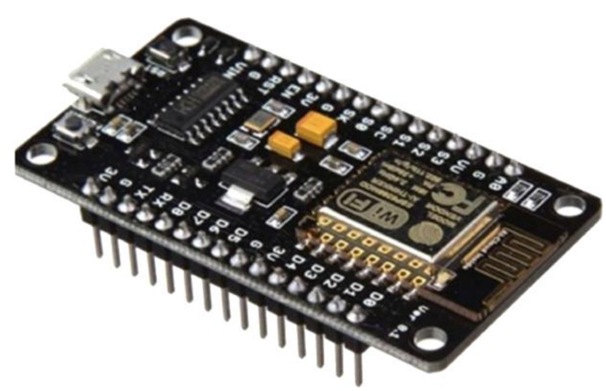

Figure 5 : NodeMCU IoT Module

OLED Display

Images on OLED screens are of excellent quality, with vivid hues, quick refresh rates, and, most significantly, striking contrast. The simplicity of OLEDs makes it straightforward to manufacture bendable and see-through screens.

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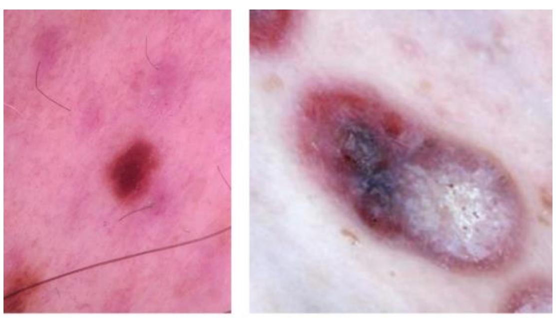
IV. DESIGN THINKING

RESULTS & IMPLEMETATION

To determine the efficacy of the hybrid model, we test it against the aforementioned database and compare the results to those obtained by using conventional methods. To evaluate the DLXG model's performance, we compare its results to those of other categorization methods applied to the same dataset. Forecasting Melanoma Skin Cancer using an unique DLXG algorithm with an accuracy rate of 94.15% is the goal. In the proposed method, Python, an open-source programming language, is used to produce the scripts needed to predict the occurrence of Melanoma Skin Cancer. This is done with the use of the Jupyter NoteBook.



(a) (b)

Figure 7 : (a) Normal and (b) MelanomaImage

Figure 7 shows a comparison of normal skin and skin with melanoma. In order to enhance the accuracy of the model during model training, hairs are eliminated from the basis picture during preprocessing. The unprocessed version of the photograph is seen in Figure 8.

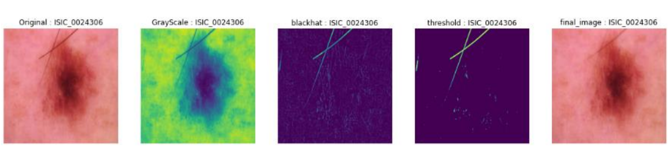


Figure 8 :Pre-Processed Image

A representation of the DLNN model's confusion matrix is presented in Figure 9. In machine learning, a confusion matrix provides quantitative insight into the factors impacting your categorization model's efficacy. It enables smarter and more well-informed decision-making. Figure 10 depicts a possible confusion matrix impression when using the proposed method and sums up the expected outcomes of a classification scenario.

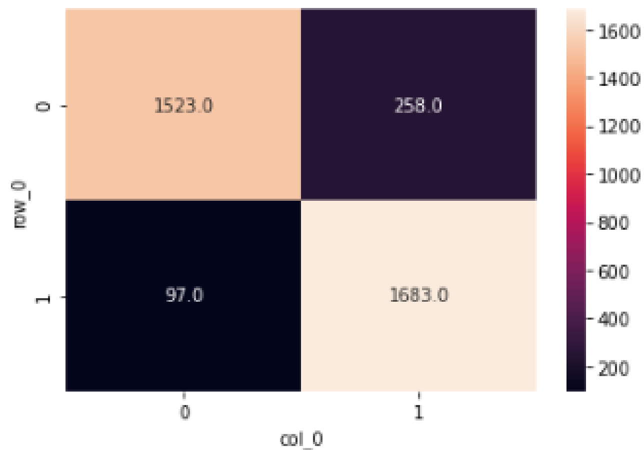


Figure 9 : Confusion Matrix of DLNN

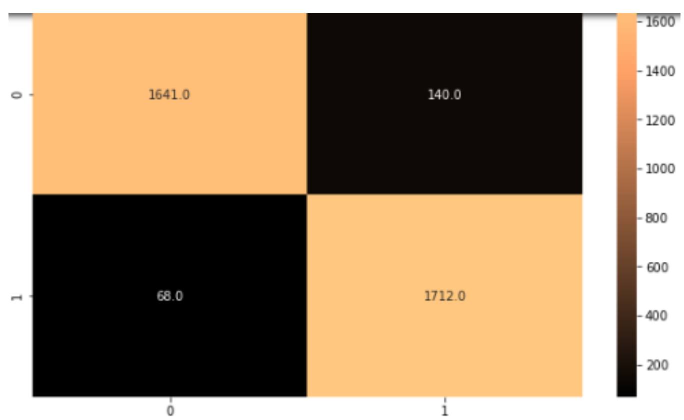


Figure 10 : Confusion Matrix of DLXG

The Training Accuracy Ratio as seen by the proposed method is depicted in Figure 11 below. Figure 12 depicts the Training Loss Ratio, which is calculated by comparing the total supply of qualifying instances to the randomly selected testing or validation inputs.

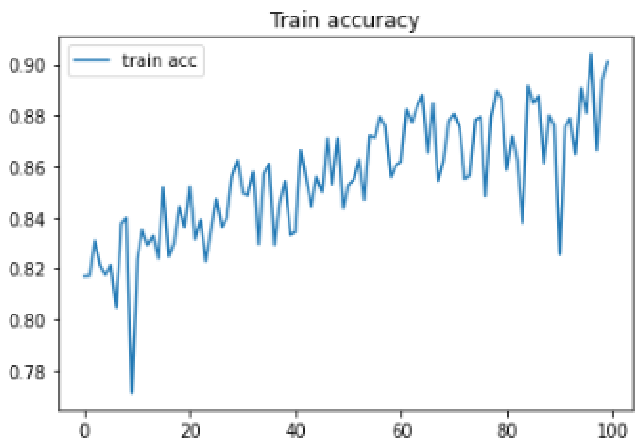


Figure 11 : Training Accuracy

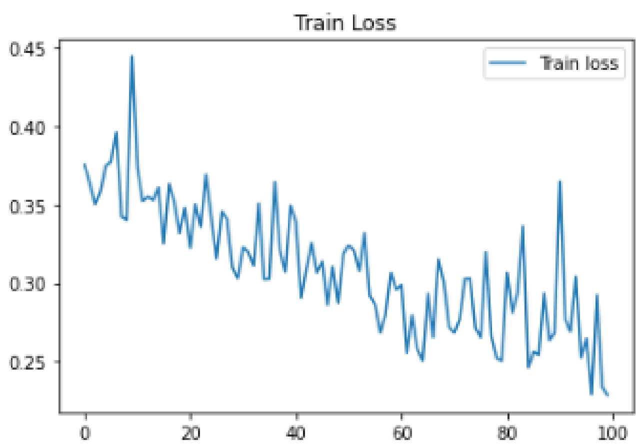


Figure 12 :Training Loss Ratio

Figure 13 compares the accuracy of the recommended CNNSVM, DLNN, and DLXG to that of their respective equivalents. The accuracy of CNNSVM was 92%, whereas that of DLNN was 90%. Our suggested approach produced a 94.15% accuracy rate, which was higher than that of any other existing approaches.

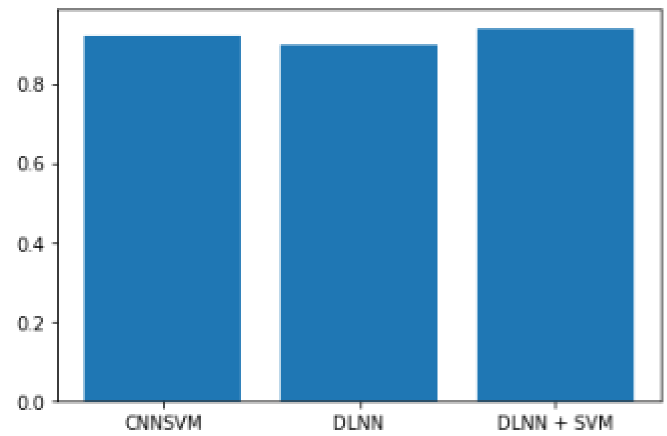


Figure 13: Accuracy Evaluation of Various Models

V. Conclusion and Future Work

While design thinking of melanoma is the most lethal form of skin cancer, if caught early enough it may be curable. Thus, it is crucial to employ diagnostic imaging techniques that have been proved to aid in and enhance the diagnostic process. Medical professionals have developed these methods in an effort to detect melanoma at an early stage. In this study, we present a hybrid approach to melanoma skin cancer detection that may be used to the evaluation of any worrisome lesion. Both the Deep Learning Neural Network and the XGBoost Classifier play vital roles in our Hybrid system. An accuracy score of 94.15 percent was achieved by the suggested Model. As demonstrated by a comparison to prior approaches like CNNSVM (92%) and DLNN (90%), our suggested method enhances accuracy and may be used to aid in the classification of Melanoma skin cancer. Ensembled Deep learning models may be used in the future to improve the job and increase the categorization accuracy rate, making illness predictions more accurate and dependable.

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