



REVA
UNIVERSITY

Bengaluru, India

**A Project Report on
Identify Melanoma using CNN**

**Submitted in Partial Fulfilment for Award of Degree of
Master of Business Administration
In Business Analytics**

**Submitted By
Shashidhara G. M
R18DM057**

**Under the Guidance of
Akshay Kulkarni
Manager Data Science& AI,
PublicisSapient**

REVA Academy for Corporate Excellence - RACE
REVA University
Rukmini Knowledge Park, Kattigenahalli, Yelahanka, Bengaluru - 560 064
race.reva.edu.in

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Candidate's Declaration

I, **Shashidhara G M** hereby declare that I have completed the project work towards the second year of Master of Business Administration in Business Analytics at REVA University on the topic entitled **Identify Melanoma using CNN** under the supervision of **Akshay Kulkarni**. This report embodies the original work done by me in partial fulfillment of the requirements for the award of a degree for the academic year **2022**.

Place: Bengaluru

Name of the Student: **Shashidhara G M**

A blue ink signature of the student's name.

Date: 27 August 2022

Signature of Student



Certificate

This is to Certify that the Project work entitled **Identify Melanoma using CNN** carried out by **Shashidhara G M** with **SRN R18DM057**, is a bonafide student of REVA University, is submitting the second year project report in fulfillment for the award of **Master of Business Administration in Business Analytics** during the academic year **2022**. The Project report has been tested for plagiarism and has passed the plagiarism test with a similarity score of less than 15%. The project report has been approved as it satisfies the academic requirements in respect of project work prescribed for the said Degree.

Akshay Kulkarni

Signature of the Guide

Signature of the Director

Akshay Kulkarni

Name of the Guide

Dr. Shinu Abhi

Name of the Director

External Viva

Names of the Examiners

1. Dr. Sai Hareesh, Research Expert, SAP Labs India
2. Pradeepa Mishra, Director – AI, L&T InfoTech

Place: Bengaluru

Date: 27 August 2022



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Place: Bengaluru

Date: 27 August 2022



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Date: 27 August 2022

Signature of Student

Verified by:

Signature

Dr. Shinu Abhi

Director, Corporate Training

List of Abbreviations

Sl. No	Abbreviation	Long Form
1	ISIC	International Skin Imaging Collaboration
2	AUC	Area Under the Curve
3	ROC	Receiver Operating Characteristic
4	ML	Machine Learning
5	CNN	Convolutional Neural Network
6	DNN	Deep Neural Network
7	DL	Deep Learning
8	NN	Neural Network
9	ISBI	International Symposium on Biomedical Imaging
10	ANN	Artificial Neural Network
11	UVA	Ultraviolet A (related to skin aging)
12	UVB	Ultraviolet B (related to skin burns)
13	MLP	Multilayer Perceptron
14	TDS	Total Dermoscopic Score

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Abstract

Skin cancer is a common disease that affects mankind significantly every year there are more new cases of skin cancer than the combined incidence of cancers of the breast, prostate, lung, and colon. With over 5,000,000 new cases every year skin cancer is a concerning public health predicament. Melanoma and non-melanoma are the two main kinds of skin cancer, respectively. Melanoma is a malignant tumour. The 19th most common malignancy in both men and women is melanoma. The deadliest types of skin cancer are melanoma, which can spread quickly.

The crucial factor in Melanoma cancer treatment is early diagnosis. Doctors usually prefer the biopsy method for skin cancer detection. During a biopsy, a sample from a suspected skin lesion is removed for medical examination to determine if it is cancerous or not a biopsy is a painful, slow, and time-consuming method.

Using current age technology and computers enabled machine learning /deep learning is proposed which can diagnose skin cancer symptoms easily. It is less expensive and can be diagnosed speedily. The moles are examined to check if they are melanoma or benign/Nevus through a noninvasive procedure. This study proposes a end to end decision based system classifiers for example like neural networks. Convolutional neural networks will be used to classify melanoma or benign. CNN architectures are appropriate classifiers to distinguish between the images of moles on the skin. This study has used images from both clinical and dermoscopic images Med-node and ISIC. The procedure advised in Melanoma detection shall capture images and preprocess. Segment the acquired preprocessed image and extract the desired feature and classify them as Melanoma or benign. The model has given an accuracy of 94 %, Sensitivity and Specificity are at 0.87 and 0.89 respectively.

The novelty of this study is that by using CNN the doctors can early detect melanoma cancerous symptoms and start the medication.

Keywords: Image processing, Deep learning, Convolutional Neural Network, Skin lesion detection, Neural network.

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Chapter 1: Introduction

Melanoma is one among the many deadly category of the skin related cancer. Occurs when melanocytes (these are the cells that provides the skin its brown or tan color) it may start growing out of control. Malignant melanoma is also one of the fastest - growing cancers (American Cancer Society, 2020).

Melanoma is not much common compared to many other types of skin cancers. Melanoma is very dangerous because it is most likely to spread to the various other parts of the human body if not detected early and treated. Most skin cancers start from the top layer of the skin called epidermis. The 3 main known types of cells in the skin layer are Squamous cells, Basal cells, and Melanocytes as shown in skin cell Figure No. 1.1.

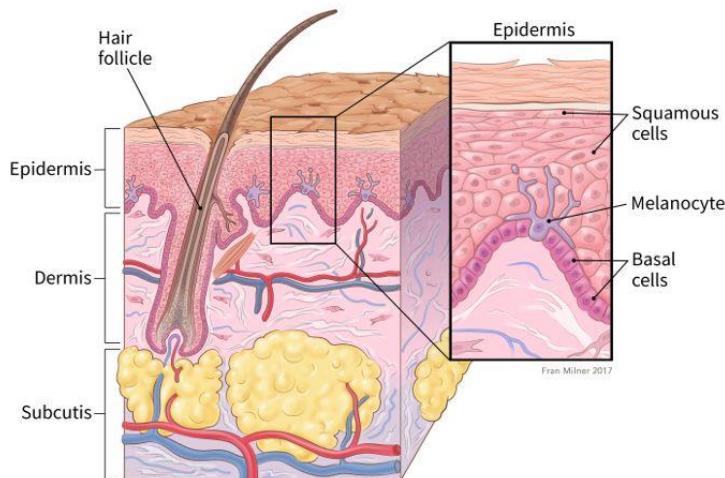


Figure No. 1.1 Skin Cell (American Cancer Society, 2020)

Melanocytes are the cells that have a high potential of turning into melanoma. These cells generally produce a brown color pigment called melanin which makes skin color tan or brown. Melanin protects the skin's deeper layers from some of the harmful effects of the sun. Melanoma is also called by different names like malignant melanoma and cutaneous melanoma. Melanin is still produced by most of the melanoma cells, tumors of melanoma are usually noticeable in brown or black. Melanomas may develop on the skin. The neck and face are other commonly known places for Melanoma to start.

Some of the exemptions is that skin with darkly pigmented lowers the risk of melanoma in the common places. Chances of getting melanoma on the feet soles, on palms, or under nails are very high. Melanomas are also seen in other parts of the body for example mouth, eyes, anal and genitals.

A mole (nevus) is a benign tumour on the skin developed from melanocytes. Every human being may have some moles. Many of the moles (nevi) could be harmless but few of them can turn into melanoma.

Spitz nevus another type of mole sometimes may look similar to melanoma. Spitz Nevus mostly seen in children and teens and to some extent in adults as well. These nevus tumours are normally benign and may not evolve into melanoma. Many a times physicians have challenges in determining spitz nevus from the actual melanomas.

Normal moles A typical mole on the skin is often brown, tan, or black in colour. A mole can have a circular or oval shape and can be elevated or flat. Moles often measure less than 6 millimetres (1/4 inch) in diameter. While many moles first occur during childhood or as an adult, other moles are present from birth. The mole will typically remain the same size, colour, and shape for many years after it has developed. Some moles might disappear in the future. The majority of people have a mole, and many are benign. However, it's crucial to keep an eye out for and be aware of changes in a mole's size, colour, form, and texture.



(a)

(b)

Figure 1.2 (a) Benign Mole and Figure (b) Malignant Mole (*ISIC Archive, 2019*)

Potential symptoms and visual signs of melanoma:

The most significant indications of melanoma is a new mole coming on the skin and or an existing mole that's begin to change in color, size, and shape. The differences as shown in Figure No. 1.2 (a) and (b) Benign Mole and Malignant Mole explain that a small mole can become big and change into a dark color raising the mole height as well.

As per the data provided by the WHO and the other International Agency who does primarily research on cancer through cancer study project called Globocan, the worldwide incidence rate of melanoma is growing at a steady rate. Around 25-30% of Romanian patients are detected with Malignant Melanoma in advanced stages of 3 and 4 which is a very high risk. As per the 2019 American Cancer annual report it was forecasted that nearly 96,480 new cases of malignant melanoma will be added and a round 7230 people will suffer which may result in mortality from the skin disease (Medhat et al., 2022).

Suspicious melanoma is raised by physically visible tumors with the following features, uneven mole surface, fast growth in mole extent, irregular shapes with varied skin color changing from brown color to black color, and with the existence of pigmentation spots. After diagnosis by a dermatologist, it is determined by making biopsy of the examined tumor.

Across the globe, dermatologist advises conducting biopsy and the issue is that the biopsy extraction of the affected skin lesion is an old invasive method that is very painful for the patients. However, if a dermatologist is able to detect and remove the mole early on time more than 90% of malignant melanoma cases can be easily cured. If in case the melanoma skin disease is identified and not treated immediately there would be chances of spreading to the other organs such as liver or lung tumor the existence rate of the patients after surgical operation drops below 20%. With all these challenges on hand, a non-invasive computer-enabled decision system that will help patients in detecting melanoma is the need of the hour.

Estimated cumulative risk of mortality in 2020, melanoma of skin, both sexes, all ages

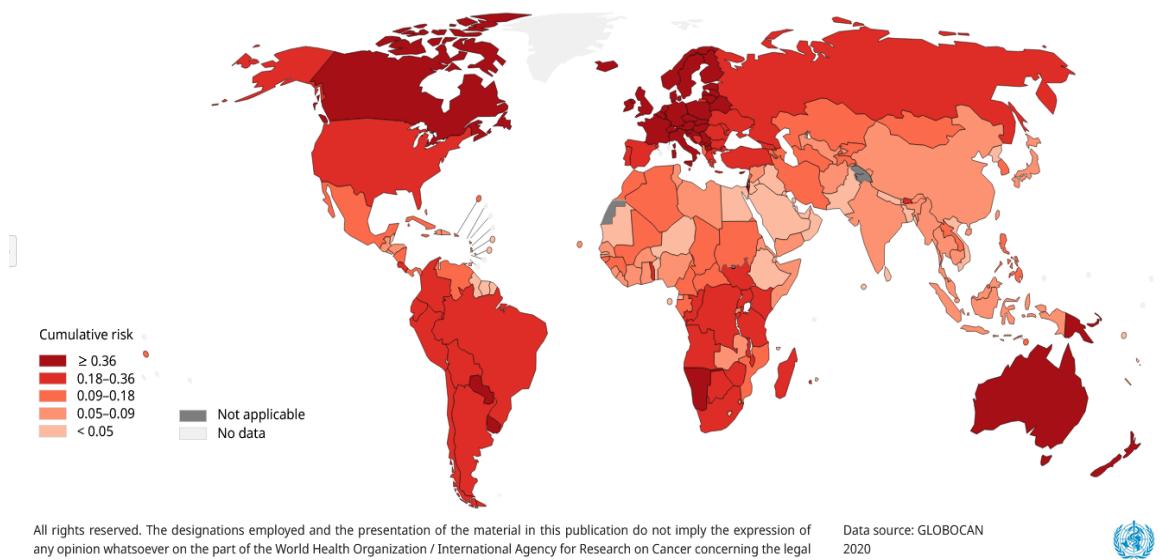


Figure No. 1.3 Melanoma Mortality Rate across Globe (Global Coalition for Melanoma Patient Advocacy & Euro Melanoma, 2020)

Based on the above mortality graph Figure No. 1.3 it indicates that the disease is spread across the globe barring a few Asian countries. The Mortality density is high in the Northern Americas region, Europe, and in Australia continent. On the contrary, the data shows that this disease is also prevalent in African countries as well.

Chapter 2: Literature Review

This chapter reviews the literature to understand how Melanoma a type of Skin cancer is currently a serious health issue. It is very important to learn more about how technology plays a major role in anticipation of how chronic diseases can reach an alarming stage. For an effective systematic literature review, this study is looking for answers on what are the major deep learning techniques used for skin cancer detection, the results of such studies, and the datasets used in studies.

2.1 Understanding of Skin Cancer

Malignant Melanoma generally looks like an uneven mole. More advanced malignant melanoma may have high inflammation, ulcers or itchy bleeding lesions. But few melanomas may not have the usual tint of a mole as shown in Figure No. 2.1. These melanomas may be small less than 5 mm in size, usually the moles are large in size which are more than 5 mm. Melanomas can occur in spots that are never or rarely exposed to sunrays. In such scenario, the diagnosis is done through a local visual check of the lesion by a physician.

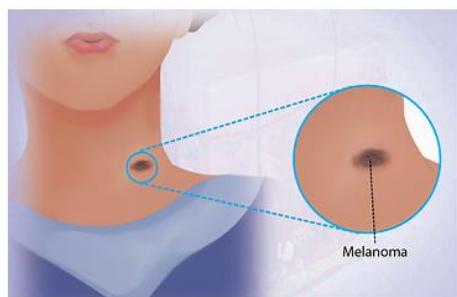


Figure No. 2.1 Melanoma (American Cancer Society, 2020)

2.2 Etiology

The probable causes of skin cancer Melanoma may be related to:

- Family history of having Melanoma – 5% to 10% of patients having family history have a 2.2 -fold higher risk of getting impacted with melanoma
- Sunburns High ultraviolet B (UVB) and ultraviolet A (UVA) radiation exposure, Sunscreen may block UVB in people using sunscreen

- Socioeconomic status - due to Lower socioeconomic status and unavailability of clinical resources may lead to a advanced stage of disease (Heistein & Acharya, 2021).

The dermatologists use ABCDE rule as guide to identify signs of melanoma as shown in Figure No.2.2. A patient has to monitor the skin moles developing and needs to share with the doctor any of the following features,

	A – Asymmetrical Shape Melanoma lesions are often irregular, or not symmetrical, in shape. Benign moles are usually symmetrical.
	B – Border Typically, non-cancerous moles have smooth, even borders. Melanoma lesions usually have irregular borders that are difficult to define.
	C – Color The presence of more than one color (blue, black, brown, tan, etc.) or the uneven distribution of color can sometimes be a warning sign of melanoma. Benign moles are usually a single shade of brown or tan.
	D – Diameter Melanoma lesions are often greater than 6 millimeters in diameter (about the size of a pencil eraser).
E	E – Evolution (or Change) The evolution of your mole(s) has become the most important factor to consider when it comes to diagnosing a melanoma . Knowing what is normal for YOU could save your life.

Figure No. 2.2 ABCDE rule of Melanoma (Jin & Oakley, 2019)

Few melanomas may not easily fit ABCD rules. It's very important to appraise the physician on any changes or varying moles and new moles being developed on the skin that look very different from the rest of the moles present in the body.

Other warning signs for Identifying Melanoma are,

- Changes in sensation like itching, pain, changing the surface of a mole, bleeding, or the appearance of a lump or bump
- A sore that doesn't heal for a long time
- Gradual Spread of pigment from the border of an existing mole into the surrounding skin
- Redness or a new beginning of swelling beyond the border of the mole

Even for dermatologists many a times it is very challenging to identify the varying changes between normal mole and melanoma including senior and experienced

doctors so it's very significant for patients who have suspicious moles need to visit a doctor and get diagnosed for any mole that a person is having.

Melanomas do appear in places other than the skin such as under toenails or fingernails, inside the mouth, or even in the eye, it's imperative to visit a physician on any new mole or changing area of the moles.

2.3 Technical Understanding - Convolutional Neural Network (CNN)

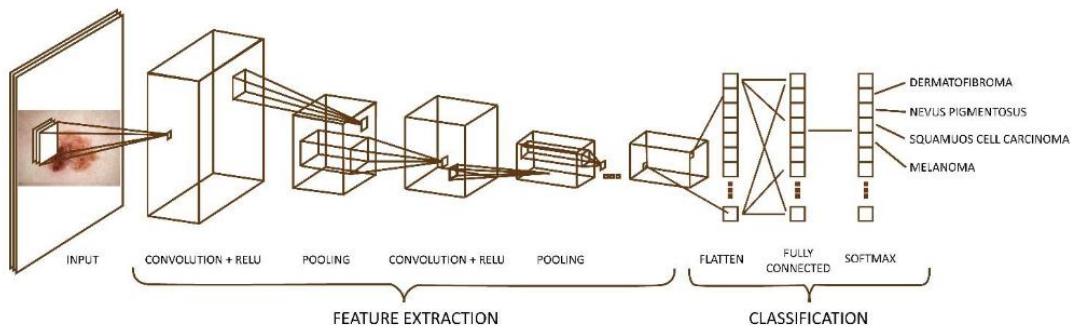


Figure No. 2.3 The Architecture of CNN (Fu’adah et al., 2020)

In order to process two-dimensional input, CNN is a Multilayer Perceptron (MLP). Because it contains a deep network and is frequently used for processing and interpreting picture, CNN is one of the types of neural networks. CNN architecture is comparable to that of neural networks in that each CNN neuron has a function for bias, weight, and activation. The CNN architecture is represented in Figure 2.3 by the convolution layer with ReLU activation. Pooling layer is employed for extracting feature, and the fully connected layer with softmax activation as the classification layer. Below, we'll briefly go over each of the CNN layers..

2.4 Convolution Layer

The first layer to process the image as an input system model is the convolution layer. The feature map is an image that has been processed using a filter to extract features from the input.

2.5 ReLU -Activation

Rectified Linear Unit is a CNN activation layer used to enhance neural network training, which has the advantage of reducing errors. Rel-U sets all of the pixels' values to zero when a pixel picture contains a value other than zero (Agarap, 2018).

The pooling layer has various advantages, including the ability to gradually reduce volume of the output on the feature map and the ability to control over-fitting. It is typically introduced after several convolution layers in the CNN method (Kim, 2017). The pooling layer also reduces the amount of computation only needed to run in the network and the number of parameters to make learners use.

A convolution layer's features map summarizes the features that are present in a particular region. The ensuing operations are performed on summarized features rather than the precisely positioned features that are created by the convolution layer.

This advantage makes the model more resilient to alterations in the arrangement of the features in the input image.

Utilizing maximum or mean pooling, data is reduced utilizing the pooling layer. In contrast to mean pooling, which chooses the average value, max-pooling will choose the maximum value as depicted in Figure No. 2.5.

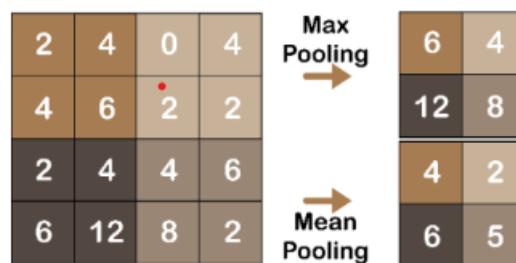


Figure No. 2.5 Pooling Process Illustration (Fu’adah et al., 2020)

2.6 Hyperparameter

The performance of the model can be impacted by the hyperparameter, which has changing values that persist during the training of model. Adaptive Moment Estimation and Nesterov-accelerated Adaptive Moment Estimation , Stochastic Gradient Descent (SGD), Root Mean Square Propagation (RMSprop), are examples of hyperparameters that are frequently employed as optimizers (Nadam).

A recurrent optimization technique called stochastic gradient descent (SGD) aims to improve the model by applying superior functions like differential or subdifferential. Each training sample is treated as a new parameter by SGD. A common technique for creating deep learning models is called Root Mean Square Propagation (RMSprop) (Duchi et al., 2012).

This optimizer is a variation on the Root Propagation algorithm (Rprop). Rprop can't initially be applied to files containing a lot of data. Moving the gradient average at the model's time is the core of RMSprop. RMSprop and momentum are combined to create the Adam optimizer. Additionally, this optimizer employs an average weight gradient (Yu & Liu, 2019).

Adam will be used in this research, compared to other optimizers, Adam is faster and utilizes less memory, and also can handle noisy issues with sparse gradients. Thus, Adam and NAG are combined to create Nadam (Nesterov-accelerated Adaptive Moment Estimation) (Nesterov accelerated gradient).

2.7 Literature Study

Over time different researchers have worked on skin lesion detection systems using machine learning and deep learning techniques.

Melanoma skin cancer if detected early the disease can be cured. In this study, a solution for detecting early-stage melanoma skin cancer using CNN is worked. Image processing is done on 514 raw images from ISIC archive for training and validating our

model. The experimental results achieved 74.76% accuracy and 57.56% validation loss (Aima & Sharma, 2019).

During feature extraction to get object segmentation or identification is the key step, Mobilenet-V2 performs well. Smart mobile phones will use the proposed model in this study. A framework with limited main memory access is required, and Mobilenet-V2 offers this feature (Sandler et al., 2018).

Transfer learning makes it possible to apply the insights obtained from earlier experiments to brand-new issues. The Resnet50, Alex-net, and Mobilenet-V2 pre-trained networks are used in this paper to implement transfer learning. The capacity to use various preprocessing techniques, such as scaling, rotation, and reflection, is provided by image data augmentation. Previous studies have shown that data augmentation improves the models' accuracy (Pham et al., 2020).

Both hand-coded characteristics and deep learning features were employed by the researchers. The suggested method aims to find and categorise melanoma or nevi into two classifications. 76% accuracy was attained using the ISBI 2016 dataset (Gutman et al., 2016). Some studies integrate different classifiers with convolutional neural networks CNN.

Segmentation techniques have been applied in CNN such as in (Ashraf et al., 2022). In this study, Region Of Interest (ROI) is detected through k-means and then CNN. This research achieved 97% accuracy. The model is applied on (DermIS, October 2021) and (DermQuest, 2021).

ReLU a non-linear activation function is used to ease the problem of gradient disappearance and as an optimized RMSprop/Adam is used for the loss algorithm. Between the convolution layer and the activation layer a normalization layer is added to solve the gradient disappearance and explosion. Neural network provides higher accuracy for the melanoma images segmentation as compared with existing processes (X. Zhang, 2017).

The study is having dataset of 2,056 patients (20.8% with a minimum of one melanoma, 79.2% with zero melanomas) across three continents averaging 16 lesions per patient,

consisting of 33,126 dermoscopic images and 584 (1.8%) histopathologically confirmed melanomas compared with benign melanoma mimicking data (Rotemberg et al., 2021).

In this study, an ensemble learning approach combines three DCNNs architectures such as Inception V3, Inception ResNet V2, and DenseNet. This model produces good classification performance with 97.23% accuracy, 90.12% sensitivity, 97.73% specificity, 82.01% precision, and 85.01% F1-Score. This method gives encouraging results in classifying skin lesions for cancer diagnosis (Pratiwi et al., 2021).

Real-time image augmentation with the algorithm-level method of designing a new loss function. The training dataset has 24,530 dermoscopic images. The proposed EfficientNetB4-CLF model gives the highest accuracy of 89.97% and also the highest mean recall of 86.13% (Pham et al., 2020).

Generic algorithms can be used to successfully identify appropriate architectures for the diagnosis of melanoma, resulting in an overall prediction performance improvement of 11% and 13%. To help dermatologists, the suggestion was turned into an online application. (Pérez & Ventura, 2021).

In this study, two techniques are used to categorise the stages of melanoma cancer. Stage 1 and stage 2 melanoma are categorized using the first technique. The second technique divides melanoma into three stages: stage 1, stage 2, and stage 3. The suggested system employs the Similarity Measure for Text Processing (SMTP) loss function and a convolutional neural network (CNN) algorithm. The exhibited and compared experimental findings with various loss functions include the proposed SMTP loss function (Patil & Bellary, 2022).

Images of the dermoscopic kind, containing various cancer samples, are gathered for this investigation from the databanks (ISIC 2016, ISIC2017, and ISIC 2020). Model has been assessed using F1 score, recall, specificity, recall, precision, and accuracy. Accuracy rates for the proposed DCNN classifier were 81.41%, 88.23%, and 90.42% (Kaur et al., 2022).

To analyze the performance of the Deep Generative Adversarial Network developed two CNN models to function simultaneously based on the architecture of ResNet50 and VGG16. DGAN performed very good on the conventional data augmentation by having a performance of 91.1% for the unlabeled dataset and 92.3% for the labeled dataset. On the other side, CNN models with data augmentation performance was at 70.8% for the unlabeled dataset (Heenaye-Mamode Khan et al., 2022).

This study limits review to skin cancer classifiers. In particular, CNN for segmentation or for the classification of dermoscopic patterns is not considered here. Further this study dwells upon why the comparability of the presented procedures is very difficult and what type of challenges has to be addressed in the future (Brinker et al., 2018).

This Paper has reviewed studies on (AI/ML) algorithms aiming to facilitate the early diagnosis of skin cancers. Researchers evaluated MEDLINE, Embase, Scopus, and Web of Science (from Jan 1, 2000, to Aug 9, 2021) further and have published the summary.

	Sensitivity	Specificity	Positive predictive value	Negative predictive value	Area under the receiver operating characteristic curve	Accuracy*	F1-score†
Melanoma (197 studies provided outcome measures for melanoma alone, 2000–21)							
Mean (95% CI)	0.842 (0.816-0.868)	0.891 (0.871-0.910)	0.814 (0.769-0.859)	0.929 (0.909-0.949)	0.898 (0.882-0.915)	89.5% (88.2-90.8%)	0.807 (0.732-0.882)
Median (IQR)	0.894 (0.792-0.950)	0.920 (0.850-0.965)	0.846 (0.720-0.955)	0.930 (0.900-0.960)	0.910 (0.849-0.950)	91.3% (86.0-95.0%)	0.850 (0.748-0.960)
Range	0.13-1.00	0.36-1.00	0.280-1.000	0.86-1.00	0.71-1.00	59.7-100%	0.280-0.975
Number of studies	146	127	49	17	64	141	24
Squamous cell carcinoma (ten studies provided outcome measures for squamous cell carcinoma alone, 2015–20)							
Mean (95% CI)	0.603 (0.396-0.810)	0.933 (0.865-1.000)	0.415 (0.247-0.582)	0.951 (0.875-1.000)	0.875 (0.777-0.973)	85.3% (77.3-93.3%)	...
Median (IQR)	0.58 (0.394-0.799)	0.965 (0.928-0.979)	0.415 (0.372-0.457)	0.951 (0.931-0.970)	0.906 (0.859-0.922)	86.0% (77.5-93.8%)	...
Range	0.256-1.000	0.800-0.995	0.329-0.500	0.912-0.989	0.730-0.958	71.0-97.8%	...
Number of studies	7	5	2	2	4	4	0
Basal cell carcinoma (29 studies provided outcome measures for basal cell carcinoma alone, 2012–20)							
Mean (95% CI)	0.837 (0.792-0.883)	0.887 (0.783-0.990)	0.834 (0.767-0.902)	0.896 (0.743-1.000)	0.923 (0.879-0.967)	87.6% (80.7-94.6%)	0.846 (0.783-0.909)
Median (IQR)	0.880 (0.766-0.914)	0.938 (0.893-0.988)	0.877 (0.785-0.930)	0.978 (0.939-0.988)	0.946 (0.912-0.970)	91.1% (77.5-97.5%)	0.875 (0.845-0.913)
Range	0.580-0.996	0.342-1.000	0.541-0.986	0.510-0.992	0.76-0.99	70.0-99.7%	0.61-0.93
Number of studies	26	12	17	6	10	11	10
Benign versus malignant (33 studies involved more than two lesion types and provided outcome measures for benign vs malignant, 2018–20)							
Mean (95% CI)	0.870 (0.843-0.897)	0.864 (0.820-0.908)	0.859 (0.804-0.914)	0.892 (0.832-0.951)	0.883 (0.840-0.926)	88.8% (86.3-91.3%)	0.888 (0.817-0.959)
Median (IQR)	0.851 (0.828-0.928)	0.892 (0.842-0.923)	0.871 (0.834-0.906)	0.902 (0.874-0.939)	0.895 (0.855-0.934)	89.5% (83.8-93.1%)	0.833 (0.830-0.957)
Range	0.720-0.995	0.535-0.981	0.582-0.994	0.761-0.970	0.742-0.975	75.9-99.5%	0.826-0.994
Number of studies	28	23	14	6	12	24	5

*Accuracy index=(true positives + true negatives)/(true positives + true negatives + false positives + false negatives). †F1 score=2 × (positive predictive value × sensitivity)/(positive predictive value + sensitivity).

Table 2: Outcome measures reported in the included studies for melanoma, squamous cell carcinoma, basal cell carcinoma, and for studies that assessed the classification of benign versus malignant categories (in studies that included more than two lesion types; n=272)

Figure No. 2.7 Summary of Melanoma Studies (Mphil et al., 2021)

Chapter 3: Problem Statement

Many studies conducted have used either dermoscopic or clinical images, very minimal studies have been done using both the images together as shown in Figure No. 3.1. An inclusive model that can process any mole image and classify as melanoma or benign.

1. Medical practitioners and patients need an easy method at a faster rate in identifying the melanoma and stop the disease spreading further. Need to detect early and classify a normal mole to evolving Melanoma
2. Highly-trained specialists are required to accurately diagnose Melanoma early which is a very big challenge due to the shortage of experts.
3. Melanoma is more dangerous and has increased over the last decade and early detection of a mole becoming cutaneous melanoma will help reduce mortality rates.

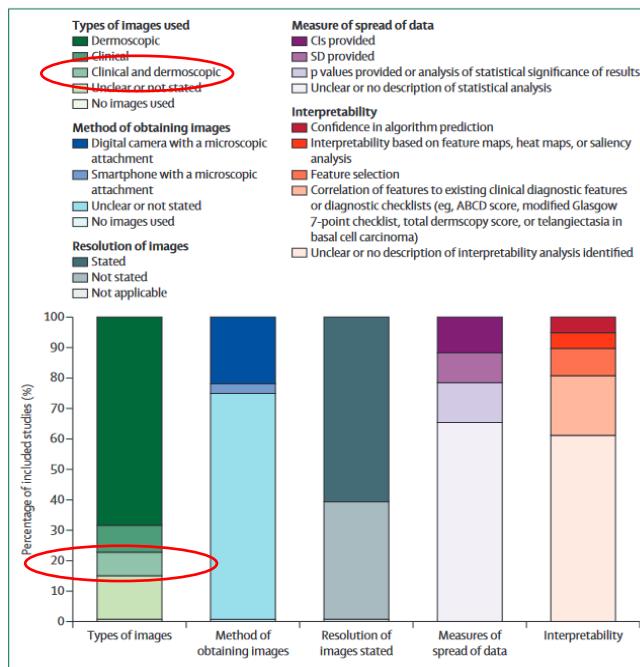


Figure No. 3.1 Number of Studies conducted based on Image sources (Mphil et al., 2021)

Chapter 4: Objectives of the Study

The objective of this study is to analyze and classify the mole images sourced either photographed using smartphone or dermoscopic device. Provide access to a computer-enabled automated, reliable system that can detect melanoma via digital images.

1. The Model using CNN shall be able to process and classify both clinical and dermoscopic images.
2. Analyze images of lesions in a very short time can be a very useful tool in the area of medical diagnosis.
3. The model with end-to-end decision system can detect melanoma patients lives can be saved at very low cost.

Chapter 5: Project Methodology

Framework: “The CRISP-DM framework has been used here for the study in this project. It is a process model which explains approaches in data mining. It is the most widely used model in analytics. It was conceived in 1996 IBM Corporation released a new methodology called Analytics Solutions Unified Method for Data Mining/Predictive Analytics (ASUM-DM). It refines and extends CRISP-DM. It consists of the following 6 steps(*Cross-Industry Standard Process for Data Mining - Wikipedia*, 2021) .

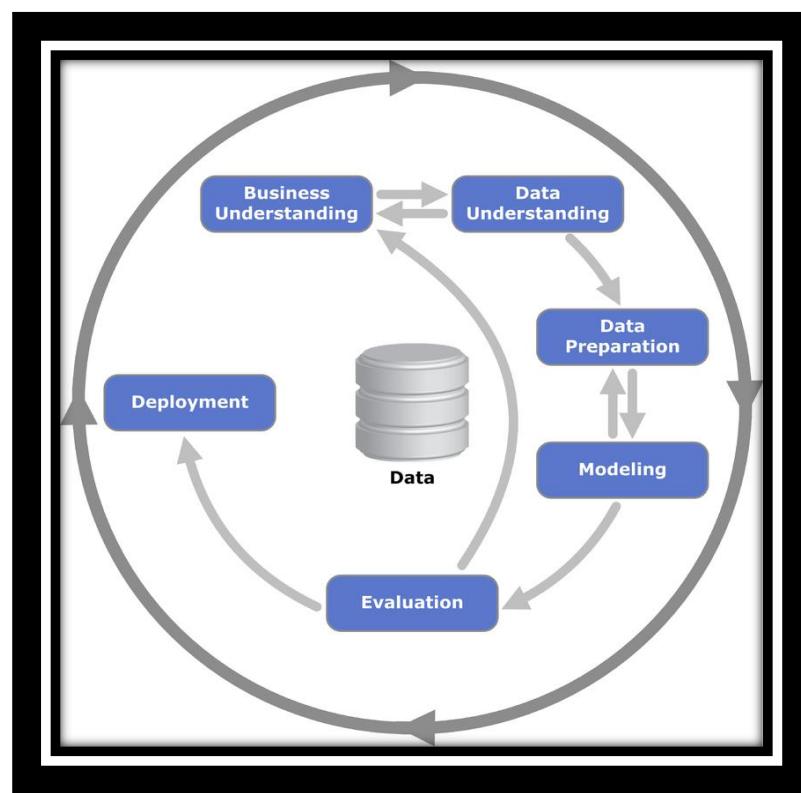


Figure No. 5.1 CRISP-DM Framework (*Cross-Industry Standard Process for Data Mining - Wikipedia*, 2021)

This study of Melanoma cancer detection using CNN has applied as per the CRISP-DM Project methodology as shown in Figure No. 5.1 and further each of the process steps is being discussed in detail from business understanding to data understanding, data preparation, modeling, model evaluation, and deployment feasibility.

5.1 Business Understanding

Melanoma is a skin growth or tumor produced due to melanocytes transformation into malignant. Melanomas usually occur on the skin. The number of cases of melanoma skin cancer diagnosed worldwide is expected to rise by 18% to 340,271 with the number of deaths increasing 20% to 72,886 by 2040.

Data Understanding

The images are sourced from ISIC and Med-node, the dermatologists use ABCDE rule as guide to identify signs of melanoma. For the study have utilized ABCD rule to identify images for the study .

Data Preparation

Images selected and labelled as benign/ nevus and melanoma , further pre-processed images before feeding into CNN model.

Modeling

CNN will be used for modeling with multiple layers with max pooling to reduce image sizes for better computing.

Evaluation

Model will be evaluated based on the Accuracy, Confusion matrix, Specificity, Sensitivity , Precision and Negative Predictive value .

Deployment

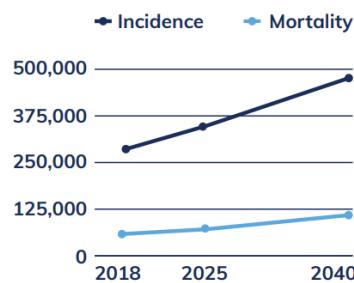
The Model will be ready however to deploy end to end solution will be part of future work.

Chapter 6: Business Understanding

Malignant melanoma is the deadliest and speedily increasing skin cancers across the globe. The easy solution would be to get diagnosed early is very much significant to get cured with a simple excision if detected early. The project objective is to develop end to end web or mobile app-based application where a Dermatologist can log into the application to detect malignant Melanoma currently the proof of concept is in progress. Below is the business analysis performed in the following categories.

6.1 Business Persona

Melanoma cases diagnosed worldwide is expected to rise by 18% to 340,271, the number of deaths increasing 20% to 72,886 by 2040. Close to half a million (466,914) people are expected to be diagnosed with melanoma skin cancer an increase of 62% against 2018 data while 105,904 are expected to die from this deadly skin cancer disease which will be an increase of 74%.



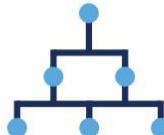
92% of people recognise that sun exposure can cause health problems.¹



But only 18% of people always protect their skin from the sun.¹

- 68% of people only protect their skin in certain situations, yet 87% of people 'always' or 'often' protect their children's skin¹

Recognising the risks



74% recognise that the risk of developing skin cancer is linked to a family history of the disease.¹



Only 11% of people have their moles checked by a dermatologist at least once a year.¹



Dermatologists say skin self-examinations should be carried out every month.

Figure No. 6.1 Mortality Trend (Global Coalition for Melanoma Patient Advocacy & Euro Melanoma, 2020)

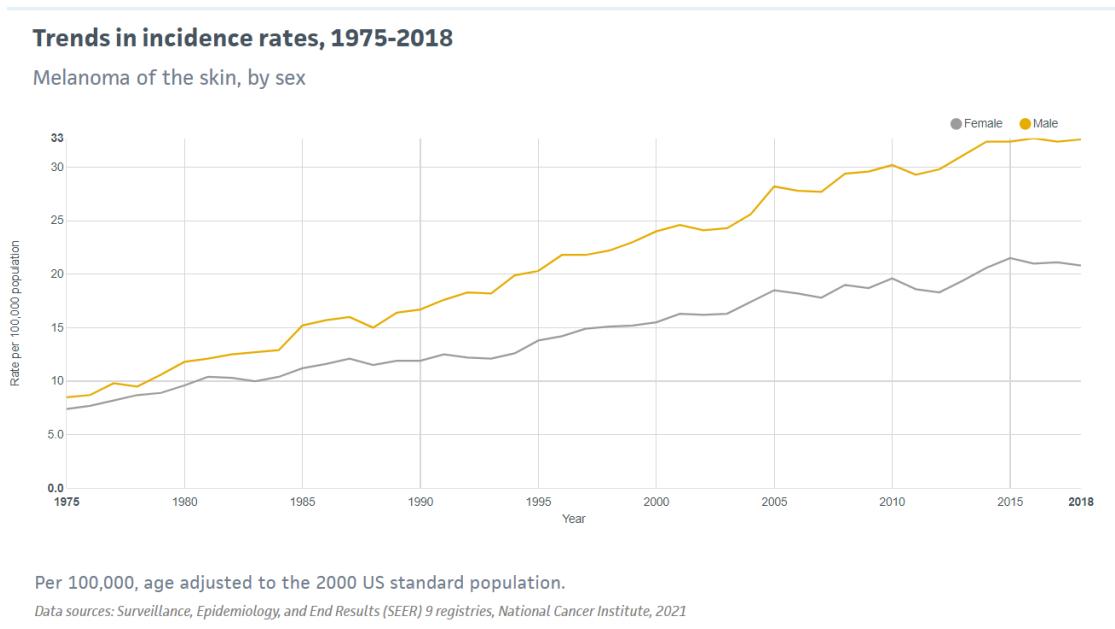


Figure No. 6.2 Melanoma Trends by Gender (American Cancer Society, 2020)

The prevalence rate is the proportion of people in the population who have a specific disease or attribute at a specific time or within a specific period (CDC Centers for Disease Control and Prevention 2019). In the United States fifth, most common cancer among men and women is melanoma. White people are more impacted with melanoma than black people which is 20 times more than later. Most women are diagnosed with melanoma much before the age of 50 however the average age of diagnosis is 65.

The development of melanoma occurs when people grow older which is a very common phenomenon. This is also seen younger population who are 30 plus age. Melanoma is the common cancer diagnosed among young adults and older people, mainly in women. Around 2400 cases estimated in 2020 are projected to be diagnosed in the age group of 15 to 29.

Skin cancer cases including melanoma have been progressively increasing for several decades. The number of melanoma diagnoses among persons in their 30s decreased somewhat for males and stayed stable for women. Increased sun protection practices and a decline in indoor tanning are probably contributing factors to the decline of melanoma among younger people.

Melanoma makes for about 1% of all skin cancer diagnoses in the US. But out of all skin cancer disorders, melanoma is the one that claims the most lives. In the United States, it is anticipated that 7,650 deaths from melanoma (5,080 males and 2,570 women) will take place. But thanks to early detection and treatment, the number of melanoma deaths fell by about 4% annually from 2015 to 2019.

Chapter 7: Data Understanding

The datasets are digital photos taken in 2018 and 2019 from a pool of consecutive lesions samples taken from the ISIC. These photographs were captured using digital cameras in a variety of resolutions while operating in nonpolarizing or polarizing modes. Images with poor image quality, ambiguity, or clarity were not included in the dataset. Figure No. 7.1 shows various examples of melanoma photos for classification. The images were manually evaluated and classified as either benign skin lesions or melanoma.



Figure No. 7.1 sample Melanoma and Nevus/ Benign Images (*ISIC Archive*, 2019) (*ISIC Archive*, 2019)

7.1 Data considered for understanding the ML models

Images were labelled as benign, naevus, and Melanoma from below sites were used from (*Dermatology Database Used in MED-NODE*, 2015), (*ISIC Archive*, 2019). 170 Images were put into the dataset relying upon their analysis label which has been extracted from the metadata of the pictures. 70 images of melanoma and 100 images labeled as nevus and benign are used in this study. 170 images are non-dermoscopic melanoma and out of that 100 are nevi. The image dimensions range from 201 x 257 to 3177 x 1333 pixels.

The dataset has been prearranged into 2 classes containing malignant melanoma Images and the other nevus images. The images from ISIC and from the Med-node archive have been chosen randomly and clubbed for the training, test, and validation.

Chapter 8: Data Preparation

8.1 Preprocessing data

When transforming images, image augmentation is a crucial technique used that may produce numerous transformed copies of the same old image. Depending on the procedures used for picture augmentation, such as shifting, rotating, flipping, etc., each image copy differs from the other images in some ways.

This technique is frequently used for creating deep learning models because applying these image augmentation in small amounts of variations on the original image does not deviate from its target class but only offers another new perspective of capturing the real object practically in day-to-day clinical life.

Images of a nevus with a raised mole with different colors of tan and brown were included. The shapes of nevi's were oval, round, dome-shaped were part of the data set. The images were largely free from hair. The ISIC data set of benign moles was in a pointed and round shape with bluish color in the background.

Malignant melanomas were a combined data set from ISIC and Mednode in equal numbers. The idea was to include the data set variation of two different sources and derive the model.

Image Data Generator By ensuring that no identical image is ever used twice during training, the image data generator will go through the image data and randomly change each unique image before it is provided to the model. Rotations, shears, flips, and zooms are just a few of the transformations that can be set when the data generator is instantiated as parameters. This transformation helps to avoid the model from learning noise in the data, such as where features are placed in the image, and makes the model more robust as it trains on slightly distorted images.

Other Challenges One another main obstacles is the big size of the images. The input feature dimension is 1760 x 1470 and the Med-node image dimensions range from 201 x 257 to 3177 x 1333 pixels. This feature size will be very big for computation to process and push to the neural network especially CNN as it also depends on the number of hidden units.

The images have three RGB (Red, Green, and Blue) channels, but because of their great computational capacity, they can only be read as a single channel. The data set's image extent is very large in both dimensions of width and height. For instance, a photograph with a width of 1760 and a height of 1470 is highly difficult to process and requires more computing power to register several pictures, which is time-consuming and wasteful of resources. The photographs must be scaled as a result of the aforementioned factors so that the machine can process the images using less memory and graphical processing resources. The approach is defined to address these two issues while reading the photos. in such a way that just one color channel is retained. Grayscale images are generated from original images for easy process.

There are three layers present in the suggested system. The input layer, which is the initial layer, here the data sets for training are placed. Information from the input layer is gathered that provides by adding weight before moving on to hidden levels. While the patterns are identified, the hidden layer's neurons extract the data's features from it. Using the patterns as foundation right classes are chosen by output layers. As last step binary classification is used, to select classes 1 and 0. Class 0 in this study denotes a benign nevus or mole, whereas class 1 denotes a malignant melanoma with cancerous cells.

Each of the preprocessed images is saved along with their classes. From the dataset, benign and malignant images are taken for further processing. Images are discarded if they are not labeled. At last, the images recorded are fed to CNN.

The CNN feature that allows you to reduce the size of the image is important and practical. By choosing a stride of 2, for example, you can confuse the image by taking into account both the horizontal and vertical orientations separately.

Pooling Layers Image size is reduced to speed up computation, pooling layers are frequently utilised. Convolutions and pulls are then applied to extract more complicated features. After features flattened to single layer images are fed to fully connected neural network of the model, The intended outcome, which is either benign or cancerous, is then discovered after using the softmax.

Chapter 9: Modeling

The pre-processing model in this study involves merely normalizing the photos, which is benign. The photos are scaled here in this step. Before processing the photos, the data must be multiplied by the rescale factor.

The proposed model would struggle to process the original images' RGB coefficients, which range from 0 to 255, at a standard learning rate, thus the values are scaled to be between 0 and 1, or 1./255, instead. In this study, the proposed CNN model as shown in Figure No. 9.1 has the first layer the convolutional (Conv2D) layer which is like a set of learnable filters opted for 32, 6x6 filters for the two first conv2D layers. Each filter transforms a part of the image (defined by the kernel size) using the kernel filter. The kernel filter matrix is applied to the whole image. Filters can be seen as a transformation of the image.

From these altered images, CNN can pick out elements that are valuable everywhere (feature maps). The pooling (MaxPool2D) layer of CNN is the second crucial layer. This layer merely serves as a down sampling filter, selecting the maximal value after examining the two nearby pixels.

These are employed to lower computational expenses and, to a lesser extent, to lower overfitting. After the first two layers followed with Max pool size 2x2 combining convolutional and pooling layers, CNN is able to combine local features and learn more global features of the image.

Dropout is a regularisation technique in which, for each training sample, a portion of the layer's nodes are randomly disregarded (their weights are assigned to zero). As a result, a piece of the network is dropped at random, forcing the network to acquire features in a distributed manner. Additionally, this method enhances generalisation and lessens overfitting. Dropout in the suggested model is set to 0.3.

'relu' is the rectifier (activation function max(2,2)). The activation of rectifier function will add non-linearity in the network. Final feature maps are converged into single ID vector by using the Flatten layer .

In order to employ fully connected layers after several convolutional/maxpool layers, this flattening step is required. It incorporates every local feature discovered in the earlier convolutional layers. Ultimately fully-connected (Dense) layer is used as an ANN classifier.

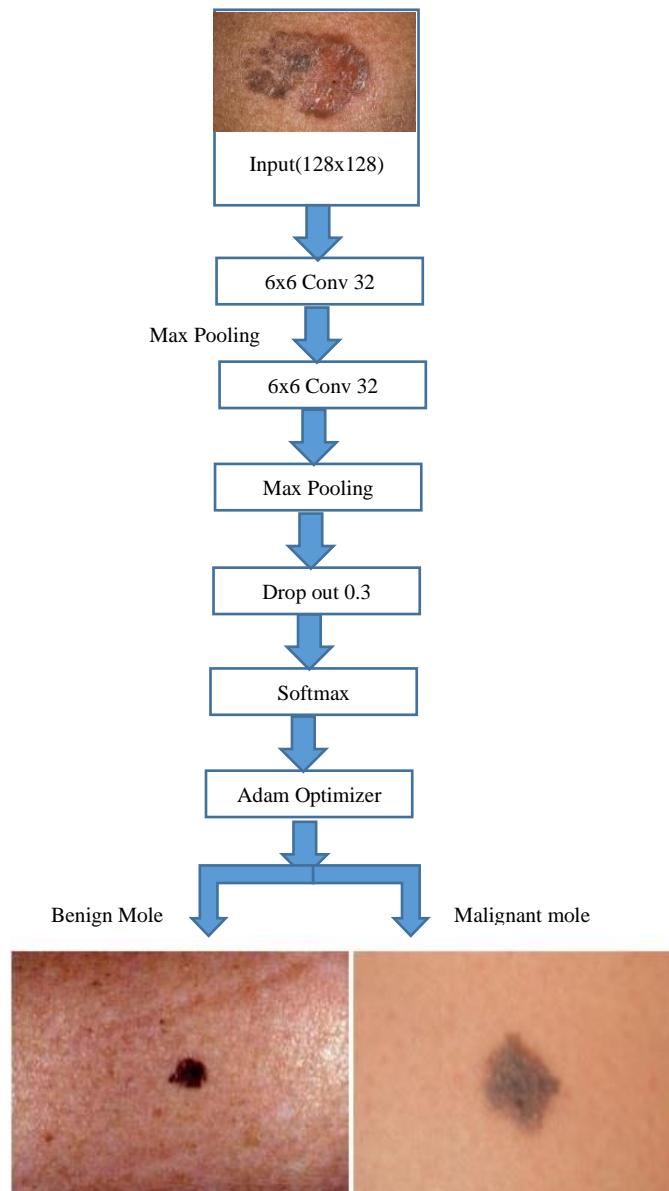


Figure No. 9.1 CNN Proposed Model

Adam optimizer provides better results. This algorithm is an extension of stochastic gradient descent adopted for deep learning applications.

Chapter 10: Model Evaluation

The iamges labeled "Naevus" and "malignant" were used. The sourced dataset has been organized into 2 classes one with Malignant Melanoma Images and the other Naevus Images with 70/30 for train and validation below is the Model summary Figure No.10.1.

Model: "sequential"		
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 123, 123, 32)	3488
max_pooling2d (MaxPooling2D)	(None, 61, 61, 32)	0
conv2d_1 (Conv2D)	(None, 56, 56, 32)	36896
max_pooling2d_1 (MaxPooling 2D)	(None, 28, 28, 32)	0
dropout (Dropout)	(None, 28, 28, 32)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 2)	50178
<hr/>		
Total params: 90,562		
Trainable params: 90,562		
Non-trainable params: 0		

Figure No. 10.1 Model Summary

From the model summary Figure 10.1 in this study, the first layer has 3488 parameters. From the above model, the summary understands that the output of each layer of Conv2D and MaxPooling2D layer is a 3D tensor of shape (height, width, channels). The dimension's width and height would shrink as learning goes deeper in the network. The first argument 32 controls the number of output channels for each Conv2D layer. The conv layers are employed to reduce the number of parameters and find local patterns. Flatten has been employed to connect conv to dense. Dropout 0.3 has been used to avoid overfitting. A dense layer has been employed after conv layers, dense layer helps in classifying the extracted features provided by conv layers. The proposed CNN model has the first layer the convolutional (Conv2D) layer which is like a set of

learnable filters, the first two conv2d layers has 32, 6 x6 filters. Using the kernel filter, each filter alters a specific area of the image. The entire image is subjected to the kernel filter matrix.

Filters can be thought of as a picture alteration. From these transformed photographs, CNN can pick out elements that are valuable everywhere (feature maps). The pooling (MaxPool2D) layer of CNN is the second crucial layer and serves as down sampling filter, choosing the maximum value from the two nearby pixels. These are employed to lower computing costs and may, to a certain extent, lower overfitting.

10.2 Model Selection

The Model has run 60 epochs as shown in Figure 10.2

```
2/2 [=====] - 5s 3s/step - loss: 0.2025 - accuracy: 0.9143 - val_loss: 0.4079 - val_accuracy: 0.8000
Epoch 48/60
2/2 [=====] - 4s 2s/step - loss: 0.2839 - accuracy: 0.8727 - val_loss: 0.4741 - val_accuracy: 0.8000
Epoch 49/60
2/2 [=====] - 4s 3s/step - loss: 0.3593 - accuracy: 0.7818 - val_loss: 0.4061 - val_accuracy: 0.8000
Epoch 50/60
2/2 [=====] - 4s 3s/step - loss: 0.2713 - accuracy: 0.9091 - val_loss: 0.3789 - val_accuracy: 0.8571
Epoch 51/60
2/2 [=====] - 4s 2s/step - loss: 0.2929 - accuracy: 0.8545 - val_loss: 0.3456 - val_accuracy: 0.8857
Epoch 52/60
2/2 [=====] - 5s 3s/step - loss: 0.1855 - accuracy: 0.9571 - val_loss: 0.3757 - val_accuracy: 0.8286
Epoch 53/60
2/2 [=====] - 4s 2s/step - loss: 0.2269 - accuracy: 0.9273 - val_loss: 0.3728 - val_accuracy: 0.8286
Epoch 54/60
2/2 [=====] - 4s 2s/step - loss: 0.1968 - accuracy: 0.8909 - val_loss: 0.3796 - val_accuracy: 0.8571
Epoch 55/60
2/2 [=====] - 5s 2s/step - loss: 0.2161 - accuracy: 0.9091 - val_loss: 0.3745 - val_accuracy: 0.8571
Epoch 56/60
2/2 [=====] - 5s 2s/step - loss: 0.1236 - accuracy: 0.9818 - val_loss: 0.4384 - val_accuracy: 0.8571
Epoch 57/60
2/2 [=====] - 5s 2s/step - loss: 0.1382 - accuracy: 0.9455 - val_loss: 0.4290 - val_accuracy: 0.8286
Epoch 58/60
2/2 [=====] - 5s 3s/step - loss: 0.2206 - accuracy: 0.8909 - val_loss: 0.4533 - val_accuracy: 0.8286
Epoch 59/60
2/2 [=====] - 5s 3s/step - loss: 0.2332 - accuracy: 0.8857 - val_loss: 0.4717 - val_accuracy: 0.8000
Epoch 60/60
2/2 [=====] - 5s 3s/step - loss: 0.1774 - accuracy: 0.9429 - val_loss: 0.3819 - val_accuracy: 0.8857
```

Figure No. 10.2 Epoch Summary

The Model as shown in Figure No. 10.2 has run for 60 epochs with training loss at 0.177 and accuracy at 0.94. The model is able to learn until the 60th epoch with validation loss reducing from 0.45 to 0.38 and Validation accuracy at 0.88. This proposed CNN model has better performance even after combined two data sets from ISIC and Med-node. From the literature review, it is learned that many studies have either used one of the datasets while training the model. This model can perform better even with the images having a small mole, large moles, and raised moles with different colors of tan and brown moles.

10.3 Model Performance

The model performance in Figure No. 10.3 has achieved an accuracy of 94 % with training loss at 17.6%, The Validation loss is at 38% for the 60th Epoch and has been decreasing meanwhile the Validation accuracy is increasing which is a good indication that the model is still learning.

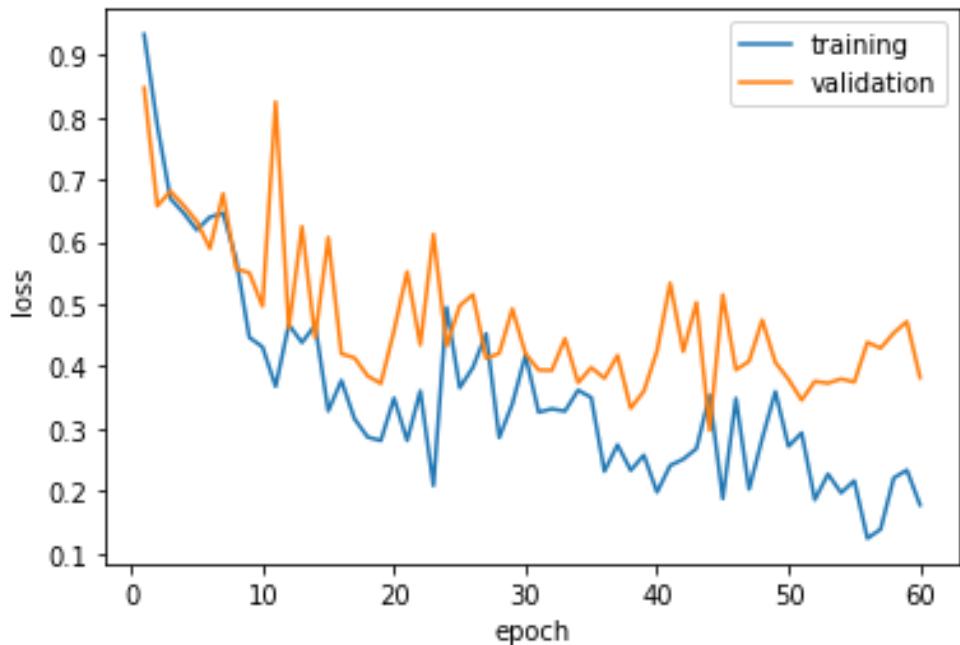


Figure No. 10.3 Training _Validation Plot

Since the validation loss is at 38% the confusion matrix as depicted in Figure No. 10.4 has very less false positives which are labeled as melanoma instead of nevus. However, the model is able to detect the true positive better. The model also is a better type II error the false negative rate is also low.

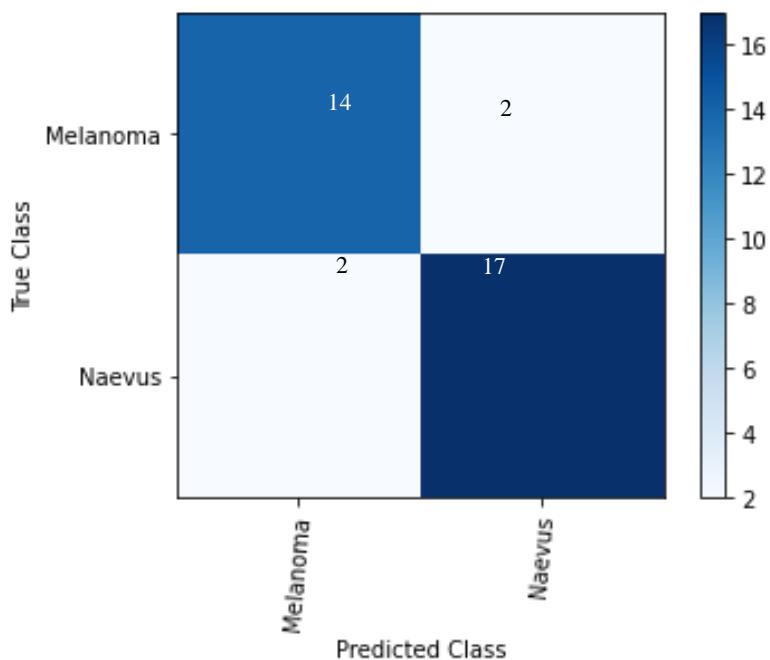


Figure No. 10.4 Confusion Matrix

Other Metrics

$$\text{Sensitivity} = \text{TP}/(\text{TP}+\text{FN}) \quad 14/(14+2) = 0.87$$

$$\text{Specificity} = \text{TN}/(\text{TN}+\text{FP}) \quad 17/(17+2) = 0.89$$

$$\text{Precision} = \text{TP}/(\text{TP}+\text{FP}) \quad 14/(14+2) = 0.87$$

$$\text{Negative Predictive Value} = \text{TN}/(\text{TN}+\text{FN}) \quad 17/(17+2) = 0.89$$

$$\text{Accuracy} = \text{TP}+\text{TN}/(\text{TP}+\text{TN}+\text{FP}+\text{FN}) \quad 14+17/(14+17+2+2) = 0.88$$

Chapter 11: Deployment

The data pipeline appears to arrange the deployment for the future as the business requirement is to create a front-end API as an application. The Complete deployment is not the scope of this project study however have considered the below deployments as a reference for future work as shown in Figure No. 11.1.

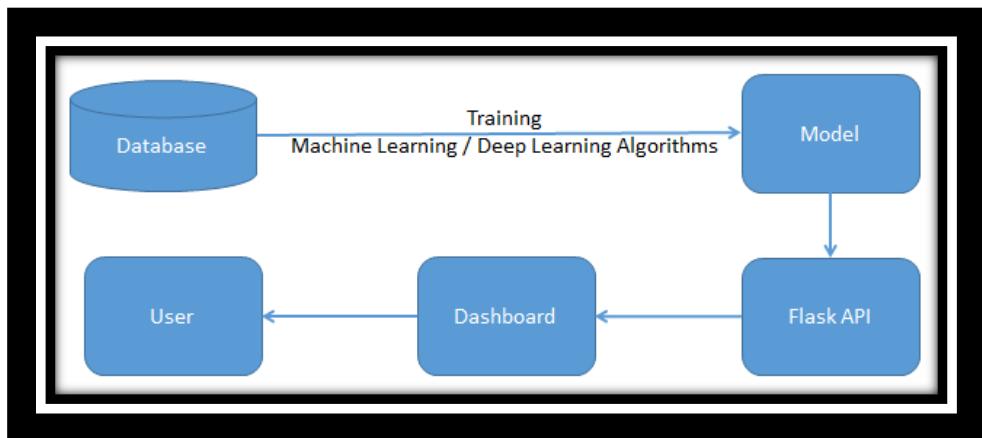


Figure No. 11.1 Deployment Proposal

The goal of this stage is to actualize end-to-end applications in which images are taken from smartphones or digital cameras and appropriately classified after the images are run through the preprocessing data generator layer and further fed through the model to detect Melanoma via a Flask API displayed in the UI / dashboard. One of the deployment- Overview of Fully Automated Approach for Early Detection of Pigmented Skin Lesion Diagnosis Using ABCD (Mabrouk et al., 2020)

Dermatologists all over the world use ABCD as the primary tool for diagnosis while patients use it as a self-examination tool and as a common reference for various skin cancer diagnosis models. This ABCD model is made up of the four main warning signs that can be detected visually and more accurately identified by the computer-embedded deep learning modeled automated system to diagnose melanoma. The features will then be detected using the ABCD rule based on the image area identified during the pre-processing and segmentation steps. In addition to the Total Dermoscopic Score (TDS) Index and three other popular machine learning classifiers, the system makes the final decision. In addition to the traditional TDS, ANN and K-nearest neighbors were used

to classify the segmented lesions. This study yields perfect results for automatically calculating the ABCD score demonstrating its viability.

The image below in Figure No. 11.2 shows how conventional methods of disease diagnosis are used by selecting a clinical view, followed by advanced methods of analyzing and detecting disease using digital cameras and deep learning models.

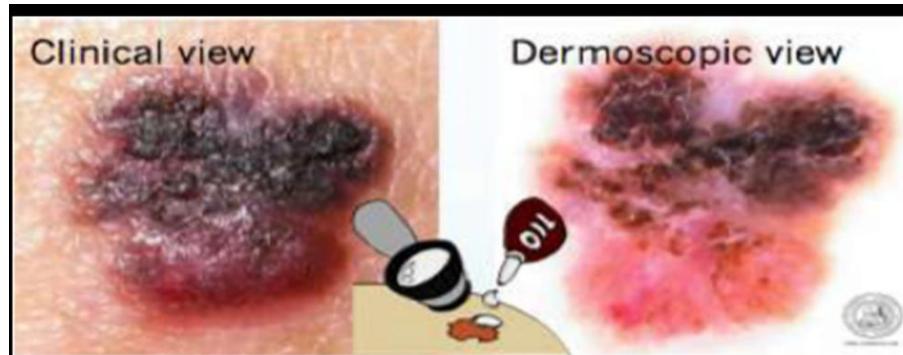


Figure 11.2 Image view normal clinical view and Smartphone view (Thapar et al., 2022)

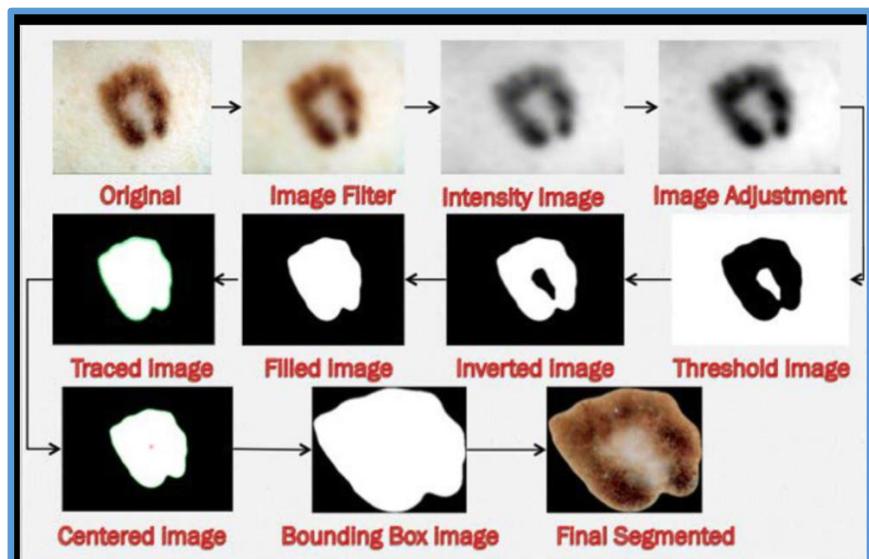


Figure 11.2.1 Image pre-processing thru Automation (Thapar et al., 2022)

Novel Hybrid Deep Learning Approach for Skin Lesion Segmentation and Classification Melanoma (Thapar et al., 2022).

Dermatologists around the world can make better decisions and diagnose Melanoma earlier by using Deep Learning techniques enabled by current technology. Melanoma, deadly cancer can be detected using advanced techniques. We can improve the model's detection accuracy over time and apply it to other skin cancer diseases. The Automation detection process will proceed as shown in Figure No. 11.2.2.

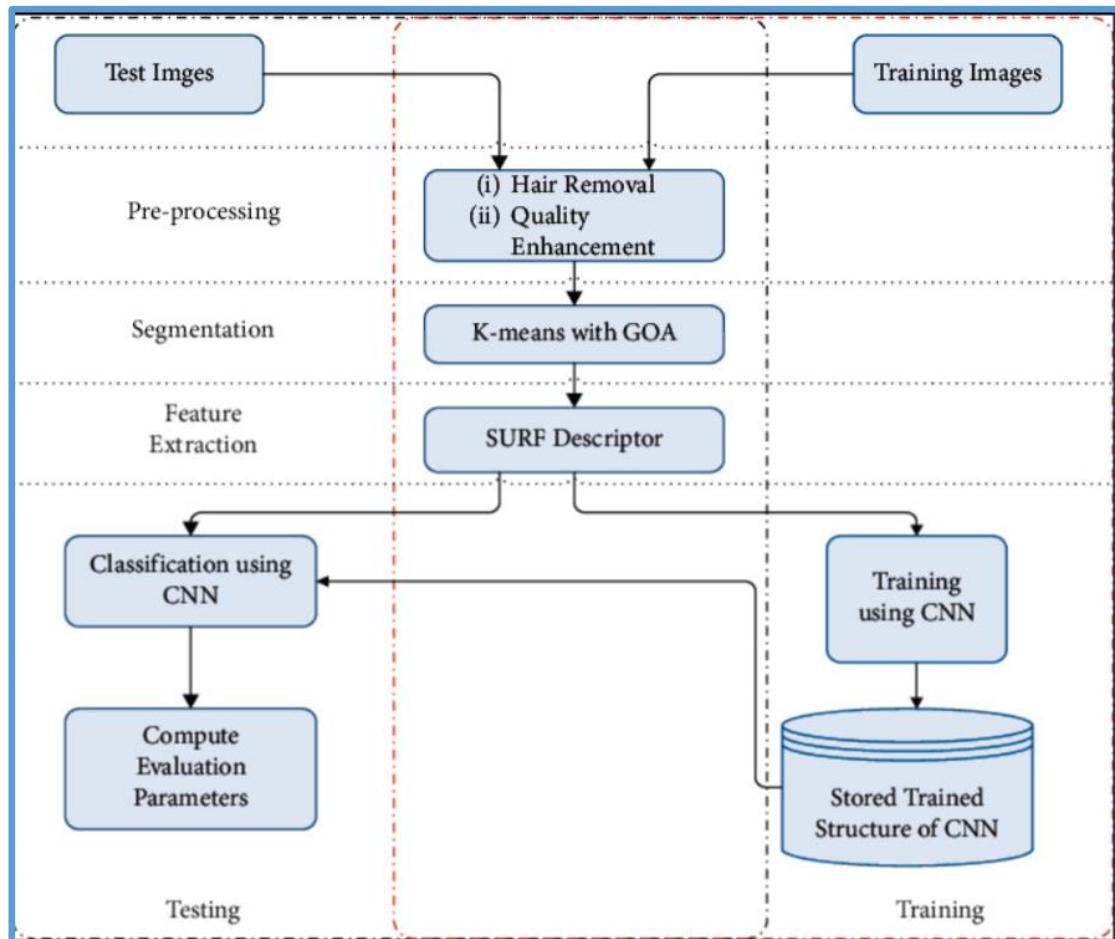


Figure 11.2.2 Lesion Segmentation and Classification of Melanoma (Thapar et al., 2022)

Chapter 12: Analysis and Results

The proposed CNN model performance on both Clinical and dermoscopic images has achieved an accuracy of 94 % with training loss at 17.6%, the validation loss is at 38% for the 60th Epoch and has been decreasing meanwhile the validation accuracy is increasing which is a good indication that the model is still learning.

Since the validation loss is at 38% as per the confusion matrix has very less false positives which are labeled as melanoma instead of nevus. However, the model is able to detect the true positive better. The model also is a better type II error the false negative rate is also low.

Overall the model is able to provide an accuracy of 0.94 which is the best among the studies done on melanoma detection particularly using images from two different data sets from ISIC and Med-node. Images class predicted from the model as shown in Figure No. 12.1.

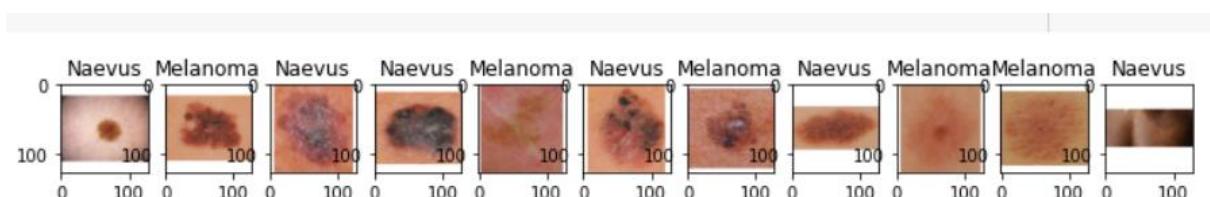


Figure No. 12.1 Predict class images

Comparing the results from literature review and from the current study are depicted in Table No. 12.2 the results from the current study are at par however the improvements have to be made in accuracy and also in classifying right class.

Results Tabulation	Specificity	Sensitivity	Precision	Negative Predictive Value	Model Accuracy
Results from this Study	0.89	0.87	0.87	0.89	0.88
Results from Literature Review	0.89	0.894		0.93	0.91

Table 12.2 Results Summary

Chapter 13: Conclusions and Future Scope

Skin cancer is a health problem that has caused concern on a global scale, and early detection of the disease is greatly aided by a reliable automatic melanoma decision system. The deep convolutional neural network that can be utilised for skin cancer classification has inspired the suggested Sequential CNN model.

The analysis's findings demonstrate that the new model is more effective than the evaluated studies and pre-trained classification models. The overall ACC for Sequential CNN is 94%.

This investigation strongly suggests using AI to identify the most deadly type of cancer since the current proposed model is good reliable in predicting the precise classification with a high true positive rate. We can speed up processing by employing images that are 128 by 128 pixels in size, have three channels, and an inference time of about 0.1 seconds per image. As a result, the suggested technique can perform even better on substantial and evenly distributed skin cancer datasets.

Future Scope

Currently, in this study we have analyzed only malignant and benign moles in the next study would like to include all types of melanomas and grade them with severity levels including data from Asian countries. Currently, the data used is from western countries (S. Zhang et al., 2021). Further would like to deploy end to end model starting from capturing images in digital cameras and a UI to process and produce the results of detection within minutes with higher accuracy.

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Publications in a Journal/Conference Presented/White Paper

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Botnet Detection in Network Traffic Based on GBM
Somesh Kumar Sahu¹, Kiran Muloor², Shashidhara G. M³, Sandeep Shyam Bajaj⁴
REVA Academy for Corporate Excellence, REVA University, Bangalore, India

Abstract: Over the past decade botnets have gained the attention of many security teams in the companies and researchers across the globe. Security teams are working tirelessly to develop systems that would detect the botnet with high accuracy in the network traffic. Botnet attacks are unique threats to systems and has high vulnerability these high risks problems naturally attracted researchers and professionals and started applying machine learning (ML) techniques to detect botnet attacks. We would like to evaluate different features and the result impact on detection accuracy for a given machine learning method used. We understand that the network traffic is being analyzed through various classification machine learning models and has given good results but we have not come across any research paper or could be less work done on Gradient Boosting Machine (GBM). We see a scope to work on GBM detecting botnet and hence propose GBM algorithm to classify the botnet traffic. In this paper, we focused only on the preprocessed botnet classified data.

Keywords: Anomaly detection, Botnet, Gradient Boosting Machine, AUC,

I. INTRODUCTION

Botnets [4] have been for a long time one of the primary security threats on the Internet and the threat risk is increasing day by day with new types of Botnet penetrating security layers. It is easy to infect a botnet in to any network, hackers today are equipped to attack quickly after exploiting new vulnerabilities. Many Machines numbering in thousands are typically part of a single botnet. Botnets are highly dynamic in nature and hard to detect because of the adapting behavior and can easily breach the most common security defenses. Botnet attacks will arise from different sources and will be of different types of adaptability will be a challenge in any model or Machine learning algorithm developed. This can be achieved by using machine learning techniques mentioned in the paper. In today's world numerous techniques exist to identify a specific kind of botnet (Telnet, IRC, P2P, Domains, etc. [7]) and the scope is very much limited to a few. Limiting the application of the model in the current IoT age. To overcome the limitations, we will be targeting on differentiating normal network traffic.

II. LITERATURE REVIEW

A study by Hoang et.al (2018) shows the botnet detection model built using machine learning techniques based on Domain Name System query data. The output on Domain Generation Algorithms botnet and Fast Flux botnet data demonstrate that most of the machine learning techniques is classification- models with an accuracy of 85%. Among all the models, the random forest algorithm has given the good results with an accuracy of 90.80%. [1] Wai, F. K. et.al (2018) used a data set which used to train a binomial classifier to detect anomaly in input traffic. The study has used techniques such as linear Support Vector Machines, Decision Tree (DT) and Random Forests (RF). Support Vector Machines builds the optimum linear hyperplane and classifies the data into two classes. RF produces lowest False Positive Rate, Decision Tree results in higher Recall and FPR. The conclusion from this study is that the DT training data doesn't have overfitting issue when compared to RF model. The results indicate that Decision Tree model turned out to be the best classifier [2]. Khan, R. U et.al (2019) analyzed most common attacks like SPAM, Port Scan, Fast Flux, IRC, Click Fraud, DDoS, Compiled and Controlled record by CTU, HTTP, Waledac, Storm and Zeus botnets. From the study it was observed that the Decision Tree algorithm had a high accuracy to detect P2P botnet traffic. [3]. Wei et al. 2016 [12] used clustering method instead of classification, which is an unsupervised machine learning technique. The work was to analyze similarity analysis malicious and benign data. (4). However, the study had very limited scope of identifying botnet from one particular host.

III. OBJECTIVE OF THE STUDY

This paper applies the Cross-Industry Standard Process for Data Mining(CRISP-DM) is a complete data mining method and a structure that gives complete view of conducting data mining in this paper. CRISP-DM has different phases in the life cycle of a data mining[22] and we have followed all those phases and explained below.

IV. BUSINESS UNDERSTANDING

IT security team's Business objective is to prevent company devices from becoming part of botnet and protect corporate assets from botnet attacks. Using Analytics the use case is to comprehend the pattern of botnet attacks and help IT, security team, to take appropriate measures in preventing malicious attacks on business. The data on number of attacks has increased by 84%, and the DDoS attacks has doubled. The average duration of the impact increased by 4.21 times, while the extremely long attacks increased massive 487% growth.[21] By 2022 there will be 1.5 mobile devices per capita. There will be 12.3 billion mobile-connected devices by 2022.[20] These data points show that the Botnet threat is increasing year by year and every second number of devices are getting added to the network. The objective of this study is to label the Network traffic and predict Normal

and Botnet traffic accurately.

V. DATA UNDERSTANDING

We have accessed online files with preprocessed data [11] this dataset has been labelled with normal, botnet attack and background traffic. It has 16 features and 71 different types of botnet samples. Files were in pcap format and we converted them into CSV format. Sample data that we have accessed which has labels and have different attributes

	Unnamed: 0	StartTime	Our_Ports	SrcAddr_Sport	DestPort	DestIP	State	Size	ToPkt	ToBytes	SrcBytes	Attack	
0	0	40388 238547	tp	197.72.248.8987	→	147.22.84.229	1080	SP,SA	0	0	184	122	0
1	1	40354 230629	tp	197.72.248.8988	→	147.22.84.229	40	SP,SA	0	0	184	122	0
2	2	40371 320997	tp	197.72.248.8986	→	147.22.84.229	80	SP,SA	0	0	184	122	0

Figure.1. Sample data

Pre-processed data considered for this experiment has 2% anomalies across the distribution of network traffic. The data is imbalanced with only 2% of anomalies this hinders the learning performance of learning models. Neglecting the unbalance data leads to negative consequences [12]. The underlying concept of supervised learning technique is that it requires appropriate data for learning. Classifiers are modeled to learn and predict. Sufficient data required for training the model otherwise it would hinder the Learning.

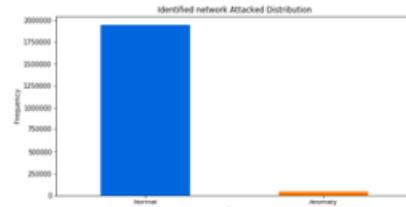


Figure.2. Actual data with 2% anomaly

VI. DATA PREPARATION

The objective of any Machine learning (ML) algorithms is minimizing errors. "Since the probability of instances belonging to the majority class is significantly high in the imbalanced data set, the algorithms are much more likely to classify new observations to the majority class" [13]. We have used the up-sampling technique to increase minority (Anomaly) data so that we can overcome the problem of overfitting of the model as the anomaly rate is only 2%[15]. In this case we have up-sampled the Minority -class to 55 % of Majority class.

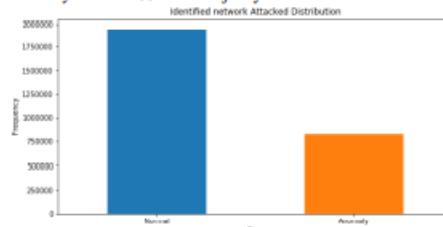


Figure.3. After up-sampling data with 55% anomaly

VII. MODELING

The botnet prediction model starts with a detailed analysis by investigating botnet features and behavioral attributes. This analysis can be generated through different classification techniques [6]. Using classifier technique, we can understand the features and behavior of Botnet. From the dataset split data for training and testing purposes. Extract the features of this dataset, we bifurcated these features into two classes, Attacked and Not Attacked. Machine learning studies how to automatically discover to make accurate predictions based on past observations. We have applied GBM (Gradient Boost Machine).

A. Classification Technique

Classification is a process of extracting the features of given data set and find out the behaviour of Botnet and its patterns for this purpose different classifier techniques are used [8]. It gives a thorough study of network traffic and determining Botnet, detects and analyzes the evidence accuracy using an efficient machine learning algorithm. The classifying process is adopted when confirmed that there is a bot in a network and it is already identified through our experimentation. Our analysis result shows the performance for findings Bot evidence using the classifiers with more detected accuracy [9]. We opted H2o GBM classifier for detecting malicious bots with higher accuracy.

B. Gradient Boosting Machine(GBM)

"GBM (Regression and Classification) is a widely used forward ML ensemble method.[14] that has demonstrated over many domains. The guideline behind GBM is to construct on weak successive trees with each tree learning and progressing on the past ones. GBM sequentially builds regression trees on all the variables of the dataset in complete each tree is built in parallel. Gradient Boosting converts decision trees as weak learners into strong learners. In boosting, trees are added without changing the existing trees. When a new tree is fit in GBM it will be done on modified version while retaining the original data set. In Gradient Boosting algorithm (GBM) algorithm starts by training a decision tree and each observation is given an equal weight. After first tree evaluation, the weights are changed either by increasing the weights of those observations that are not classified or decrease the weights of those observations that are easy to classify. Continuing the process on the reference of weighted data, the second tree is grown this improves better predictions based on the initial tree. [16] Once the new model is built with Tree 1 and Tree 2 we will derive the error from Tree 2 and build ensemble model and begin building new third tree to predict the new error. The GBM trains many models gradually and the process is additive and continuous in sequential manner. This is an iterative process subsequent trees are grown to easily classify data that were not classified correctly by the previous trees. The final ensemble model predictions are made using the previous tree models predicted weighted sum. "The GBM can also be tuned to get optimal combination of hyperparameters. Common parameters are Number of trees, depth of trees and learning rate".[5] The loss function is a measure which indicates how good the models are at fitting the original data.[18]. The GBM emphasizes on MSE where it outlines the approach of additive and sequentially fitting the trees to minimize the error. In this paper GBM H2O is used for the experiments. H2O is an open-source, in-memory, fast, and scalable machine learning helps in predictive analytics platform.[24]

VIII. RESULTS EVALUATION AND DISCUSSION

Experiments were conducted using Botnet attack records. The Botnet data contains 1997072 records out of which 40K were identified as botnet attack records which is around 2%. The current paper deals with binary classification problem, two classes (Normal, Attacked). Up-sampling applied to reduce the imbalance. In this paper, we will be examining key metrics of GBM.

Key Metrics:

- a) "MSE": It is the average squared difference between the predicted and actual target variables, and its best value is 0.0"[18]
- b) "AUC": classification model distinguishes true positives and false positives. AUC of 1 is a perfect model classifier; an AUC of 0.5 indicates a poor classifier of random guessing". [18]
- c) "Accuracy": The model accuracy is determined by the number of correct predictions made to the ratio of all possible predictions made."[18]
- d) "Cross – Validation: Cross-validation is to trim training set into k blocks, then use one of those k blocks as a validation data set, and use the rest for training. Repeat this k times, with a different part of the training set being the validation set each time".[19].

GBM Results

We have split the data into different Split of Train,Test and Valid[17] percentages.

1. Experiment 1 :Train (80%) Valid (20%)

Model Summary:

	number_of_trees	number_of_internal_trees	model_size_in_bytes		
0	50.0	50.0	14325.0		
min_depth	max_depth	mean_depth	min_leaves	max_leaves	mean_leaves
5.0	5.0	5.0	10.0	11.0	10.92

ModelMetricsBinomial: gbm
** Reported on cross-validation data. **

MSE: 1.4706742724625298e-05
RMSE: 0.003834937121339188
LogLoss: 0.0029709950596020314
Mean Per-Class Error: 1.9258360535179264e-06
AUC: 0.9999999991058406
pr_auc: 0.8005508119584737
Gini: 0.9999999982116812

Confusion Matrix (Act/Pred) for max f1 @ threshold = 0.3572584993092953:

	0	1	Error	Rate
0	0	1168229.0	16.0	0.0 (16.0/1168245.0)
1	1	0.0	615144.0	0.0 (0.0/615144.0)
Total	1168229.0	615160.0	0.0	(16.0/1783389.0)

2. Experiment 2: Train (70%) Test(15%) Valid(15%)

Model Summary:

	number_of_trees	number_of_internal_trees	model_size_in_bytes		
0	30.0	30.0	117370.0		
min_depth	max_depth	mean_depth	min_leaves	max_leaves	mean_leaves
10.0	10.0	10.0	27.0	303.0	147.83333

ModelMetricsBinomial: gbm

** Reported on train data. **

MSE: 2.9326425712147635e-09

RMSE: 5.415387863500419e-05

LogLoss: 4.9239820648439605e-05

Mean Per-Class Error: 0.0

AUC: 1.0

pr_auc: 0.9999821180081412

Gini: 1.0

Confusion Matrix (Act/Pred) for max f1 @ threshold = 0.999209123711219:

	0	1	Error	Rate
0	0	1168245.0	0.0	(0.0/1168245.0)
1	1	0.0	615144.0	0.0 (0.0/615144.0)
Total	1168245.0	615144.0	0.0	(0.0/1783389.0)

3. Experiment 3 :Train (60%) Test(20%) Valid(20%)

Model Summary:

	number_of_trees	number_of_internal_trees	model_size_in_bytes		
0	50.0	50.0	14325.0		
min_depth	max_depth	mean_depth	min_leaves	max_leaves	mean_leaves

	5.0	5.0	5.0	10.0	11.0	10.92
ModelMetricsBinomial:	gbm					

** Reported on train data. **

MSE: 1.3916525385408573e-05

RMSE: 0.003730485944941835

LogLoss: 0.00296795292530472

Mean Per-Class Error: 1.6048633779686128e-06

AUC: 0.9999999996781965

pr_auc: 0.0005391039870360671

Gini: 0.9999999999356393

Confusion Matrix (Act/Pred) for max f1 @ threshold = 0.7534551833042394:

	0	1	Error	Rate
0	0	1557760.0	5.0	0.0 (5.0/1557760.0)
1	1	0.0	819678.0	0.0 (0.0/819678.0)
Total	1557760.0	819678.0	0.0	(5.0/2377643.0)

GBM experiments on Botnet detection have given good performance with high accuracy and good botnet detection rate we have discussed two important metrics to substantiate the results.

AUC

We have carried three experiments by varying GBM hyper-parameters. The Accuracy in all three experiments is above 0.999 and in experiment 2 we have achieved AUC 1.0, higher the AUC the prediction is more accurate ranging from 0 to 1 [19]

Confusion Matrix

With different GBM hyper-parameters in all the three models the True Positives and True Negatives have been precisely classified with small error in Experiment 1 and 3. The precise classification of True positives and True negatives also mirrors with high AUC.

IX. CONCLUSION

The botnet has been a major threat to security and impacting business. The approach used in this study helps Cybersecurity teams to detect Botnet attacks proactively, increase network uptime and minimize the business impact. Based on the results using H2O GBM demonstrates high AUC ranging from 0.9999 to 1.0 and among the experiments we recommend using Experiment 2. Further we would like to expand our study in detecting different types of Botnet attacks.

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Publications in a Journal/Conference Presented/White Paper

Paper Submitted:

Shashidhara G M, Rashmi Agarwal and Jitendra Suryavamshi, "Identify Melanoma Using CNN" , EAI ICISML 2022, EAI International Conference on Intelligent Systems and Machine Learning Paper ID 324338

Identify Melanoma Using CNN

Shashidhara G M ^{1[0000-0003-1812-1540]}, Rashmi Agarwal ^{2[0000-0003-1778-7519]} and Jitendra Suryavamshi^{3[]}

REVA Academy for Corporate Excellence

REVA University, Bangalore, India

¹shashidhara.ba04@reva.edu.in

²rashmi.agarwal@reva.edu.in

³jitendra.res@reva.edu.in

Abstract. Skin cancer is a common disease that affects mankind significantly every year there are more new cases of skin cancer than the combined incidence of cancers of the breast, prostate, lung, and colon. With over 5,000,000 new cases every year skin cancer is a concerning public health predicament. Melanoma and non-melanoma are the two main kinds of skin cancer, respectively. Melanoma is a malignant tumor. The 19th most common malignancy in both men and women is melanoma. The deadliest types of skin cancer are melanoma, which can spread quickly. The crucial factor in Melanoma cancer treatment is early diagnosis. Doctors usually prefer the biopsy method for skin cancer detection. During a biopsy, a sample from a suspected skin lesion is removed for medical examination to determine if it is cancerous or not a biopsy is a painful, slow, and time-consuming method. This study proposes an end-to-end decision-based system classifiers for example like neural networks. Convolutional Neural Networks (CNN) will be used to classify melanoma or benign. CNN architectures are appropriate classifiers to distinguish between the images of moles on the skin. This study has used images from both clinical and dermoscopic images Med-node and ISIC. The procedure advised in Melanoma detection shall capture images and preprocess. Segment the acquired preprocessed image and extract the desired feature and classify them as Melanoma or benign. The model has given an accuracy of 94 %, and Sensitivity and Specificity are at 0.87 and 0.89 respectively.

Keywords: Image processing, Deep learning, Convolutional Neural Network, Skin lesion detection, Neural network.

1 Introduction

Melanoma is one among the many deadly category of the skin related cancer, occurs when melanocytes (the cells that provides the skin its brown or tan colour) may start growing out of control. Malignant melanoma is also one of the fastest growing cancers [1]. Melanomas may develop on the skin and the other commonly known places are the neck and face. Chances of getting melanoma on the feet soles, on palms, or under nails are very high. Melanomas are also seen in other parts of the body for example mouth, eyes, anal and genitals. A mole (nevus) is a benign tumor on the skin developed from melanocytes. Every human being may have some moles. Many of the moles (nevi) could be harmless but few of them can turn into melanoma. Normal moles are a typical mole on the skin is often brown, tan, or black in colour. A mole can have a circular or oval shape and can be elevated or flat. Moles often measure less than 6 millimetres (1/4 inch) in diameter. While many moles first occur during childhood or as an adult, other moles

are present from birth. The mole will typically remain the same size, colour, and shape for many years after it has developed. Some moles might disappear in the future. The majority of people have a mole, and many are benign. However, it's crucial to keep an eye out for and be aware of changes in mole's size, colour, form, and texture as shown in Fig. 1.



Fig. 1. Benign Mole and Malignant [2][3]

Across the globe, dermatologist advises conducting biopsy and the issue is that the biopsy extraction of the affected skin lesion is an old invasive method that is very painful for the patients. However, if a dermatologist is able to detect and remove the mole early on time more than 90% of malignant melanoma cases can be easily cured. If in case the melanoma skin disease is identified and not treated immediately there would be chances of spreading to the other organs such as liver or lung tumor the existence rate of the patients after surgical operation drops below 20%. With all these challenges on hand, a non-invasive computer-enabled decision system that will help patients in detecting melanoma is the need of the hour.

2 Literature Review

Over time different researchers have worked on skin lesion detection systems using machine learning and deep learning techniques. Melanoma skin cancer if detected early the disease can be cured. In this study, a solution for detecting early-stage melanoma skin cancer using CNN is worked. Image processing is done on 514 raw images from ISIC archive for training and validating our model. The experimental results achieved 74.76% accuracy and 57.56% validation loss [4].

This study is having dataset of 2,056 patients (20.8% with a minimum of one melanoma, 79.2% with zero melanomas) across three continents averaging 16 lesions per patient, consisting of 33,126 dermoscopic images and 584 (1.8%) histopathological confirmed melanomas compared with benign melanoma mimicking data [5].

In this study, an ensemble learning approach combines three DCNNs architectures such as Inception V3, Inception ResNet V2, and DenseNet. This model produces good classification performance with 97.23% accuracy, 90.12% sensitivity, 97.73%

specificity, 82.01% precision, and 85.01% F1-Score. This method gives encouraging results in classifying skin lesions for cancer diagnosis [6].

A Real-time image augmentation with the algorithm-level method of designing a new loss function. The training dataset has 24,530 dermoscopic images. The proposed EfficientNetB4-CLF model gives the highest accuracy of 89.97% and also the highest mean recall of 86.13% [7].

Generic algorithms can be used to successfully identify appropriate architectures for the diagnosis of melanoma, resulting in an overall prediction performance improvement of 11% and 13%. To help dermatologists, the suggestion was turned into an online application [8].

In this paper, two techniques are used to categorize the stages of melanoma cancer. Stage 1 and stage 2 melanoma are categorized using the first technique. The second technique divides melanoma into three stages: stage 1, stage 2, and stage 3. The suggested system employs the Similarity Measure for Text Processing (SMTP) loss function and a CNN algorithm. The exhibited and compared experimental findings with various loss functions include the proposed SMTP loss function [9].

Images of the dermoscopic kind, containing various cancer samples, are gathered for this investigation from the databanks (ISIC 2016, ISIC2017, and ISIC 2020). Model has been assessed using F1 score, recall, specificity, recall, precision, and accuracy. Accuracy rates for the proposed DCNN classifier were 81.41%, 88.23%, and 90.42% [10].

To analyze the performance of the Deep Generative Adversarial Network developed two CNN models to function simultaneously based on the architecture of ResNet50 and VGG16. DGAN performed very good on the conventional data augmentation by having a performance of 91.1% for the unlabeled dataset and 92.3% for the labeled dataset. On the other side, CNN models with data augmentation performance were at 70.8% for the unlabeled dataset [11].

This research paper limits review to skin cancer classifiers. In particular, CNN for segmentation or for the classification of dermoscopic patterns is not considered here. Further this study dwells upon why the comparability of the presented procedures is very difficult and what type of challenges has to be addressed in the future [12].

This paper has reviewed studies on (AI/ML) algorithms aiming to facilitate the early diagnosis of skin cancers. Researchers evaluated MEDLINE, Embase, Scopus, and Web of Science (from Jan 1, 2000, to Aug 9, 2021) further and have published the summary.

	Sensitivity	Specificity	Positive predictive value	Negative predictive value	Area under the receiver operating characteristic curve	Accuracy ^a	F1-score ^b
Melanoma (197 studies provided outcome measures for melanoma alone, 2000-21)							
Mean (95% CI)	0.847 (0.816-0.868)	0.891 (0.871-0.910)	0.814 (0.769-0.859)	0.929 (0.909-0.949)	0.898 (0.882-0.915)	89.5% (88.2-90.8%)	0.807 (0.732-0.882)
Median (IQR)	0.894 (0.792-0.950)	0.920 (0.850-0.965)	0.846 (0.720-0.955)	0.930 (0.900-0.960)	0.910 (0.849-0.950)	91.3% (86.0-95.0%)	0.850 (0.748-0.960)
Range	0.13-1.00	0.36-1.00	0.280-1.000	0.86-1.00	0.71-1.00	59.7-100%	0.280-0.975
Number of studies	146	127	49	17	64	141	24
Squamous cell carcinoma (ten studies provided outcome measures for squamous cell carcinoma alone, 2015-20)							
Mean (95% CI)	0.603 (0.396-0.810)	0.933 (0.865-1.000)	0.415 (0.247-0.582)	0.951 (0.875-1.000)	0.875 (0.777-0.973)	85.3% (77.3-93.3%)	—
Median (IQR)	0.58 (0.394-0.799)	0.965 (0.928-0.979)	0.415 (0.372-0.457)	0.951 (0.931-0.970)	0.906 (0.859-0.922)	86.0% (77.5-93.8%)	—
Range	0.256-1.000	0.800-0.995	0.329-0.500	0.912-0.989	0.730-0.958	71.0-97.8%	—
Number of studies	7	5	2	2	4	4	0
Basal cell carcinoma (29 studies provided outcome measures for basal cell carcinoma alone, 2012-20)							
Mean (95% CI)	0.837 (0.792-0.883)	0.887 (0.783-0.990)	0.834 (0.767-0.902)	0.896 (0.743-1.000)	0.923 (0.879-0.967)	87.6% (80.7-94.6%)	0.846 (0.783-0.909)
Median (IQR)	0.880 (0.766-0.914)	0.938 (0.893-0.988)	0.877 (0.785-0.930)	0.978 (0.939-0.988)	0.946 (0.912-0.970)	91.1% (77.5-97.5%)	0.875 (0.845-0.913)
Range	0.580-0.996	0.342-1.000	0.549-0.986	0.510-0.992	0.76-0.99	70.0-99.7%	0.61-0.93
Number of studies	26	12	17	6	10	11	10
Benign versus malignant (33 studies involved more than two lesion types and provided outcome measures for benign vs malignant, 2018-20)							
Mean (95% CI)	0.870 (0.843-0.897)	0.864 (0.820-0.908)	0.859 (0.804-0.914)	0.892 (0.832-0.951)	0.883 (0.840-0.926)	88.8% (86.3-91.3%)	0.888 (0.817-0.959)
Median (IQR)	0.851 (0.828-0.928)	0.892 (0.842-0.923)	0.871 (0.834-0.906)	0.902 (0.874-0.939)	0.895 (0.855-0.934)	89.5% (83.8-93.1%)	0.833 (0.830-0.957)
Range	0.720-0.995	0.535-0.981	0.582-0.994	0.761-0.970	0.742-0.975	75.9-99.5%	0.826-0.994
Number of studies	28	23	14	6	12	24	5

^aAccuracy index=(true positives + true negatives)/(true positives + true negatives + false positives + false negatives). ^bF1 score=2 × (positive predictive value × sensitivity)/(positive predictive value + sensitivity).

Table 2: Outcome measures reported in the included studies for melanoma, squamous cell carcinoma, basal cell carcinoma, and for studies that assessed the classification of benign versus malignant categories (in studies that included more than two lesion types; n=272)

Fig. 2. Summary of Melanoma Studies [13]

CNN in order to process two-dimensional input, CNN is a Multilayer Perceptron (MLP). Because it contains a deep network and is frequently used for processing and interpreting picture, CNN is one of the types of neural networks. CNN architecture is comparable to that of neural networks in that each CNN neuron has a function for bias, weight, and activation. In the CNN architecture the convolution layer with ReLU activation is initiated, Pooling layer is employed for extracting feature, and the fully connected layer with SoftMax activation as the classification layer. Below, the paper will briefly go over each of the CNN layers. The first layer to process the image as an input system model is the convolution layer. The feature map is an image that has been processed using a filter to extract features from the input.

ReLU (Rectified Linear Unit) is a CNN activation layer used to enhance neural network training, which has the advantage of reducing errors. Rel-U sets all of the pixels' values to zero when a pixel picture contains a value other than zero [14].

The pooling layer has various advantages, including the ability to gradually reduce volume of the output on the feature map and the ability to control over-fitting. It is typically introduced after several convolution layers in the CNN method [15].

The pooling layer also reduces the amount of computation only needed to run in the network and the number of parameters to make learners use.

A convolution layer's features map summarizes the features that are present in a particular region. The ensuing operations are performed on summarized features rather than the precisely positioned features that are created by the convolution layer. This advantage makes the model more resilient to alterations in the arrangement of the features in the input image.

Utilizing maximum or mean pooling, data is reduced utilizing the pooling layer. In contrast to mean pooling, which chooses the average value, max-pooling will choose the maximum value.

Hyperparameter:

The performance of the model can be impacted by the hyperparameter, which has changing values that persist during the training of model. Adaptive Moment Estimation and Nesterov-accelerated Adaptive Moment Estimation, Stochastic Gradient Descent (SGD), Root Mean Square Propagation (RMSprop), are examples of hyperparameters that are frequently employed as optimizers (Nadam).

A recurrent optimization technique called stochastic gradient descent (SGD) aims to improve the model by applying superior functions like differential or subdifferential. Each training sample is treated as a new parameter by SGD. A common technique for creating deep learning models is called Root Mean Square Propagation (RMSprop) [16].

This optimizer is a variation on the Root Propagation algorithm (Rprop). Rprop cannot initially be applied to files containing a lot of data. Moving the gradient average at the model's time is the core of RMSprop. RMSprop and momentum are combined to create the Adam optimizer. Additionally, this optimizer employs an average weight gradient [17].

Adam will be used in this research, compared to other optimizers, Adam is fast and utilizes less memory, and also can handle noisy issues with sparse gradients. Thus, Adam and NAG are combined to create Nadam (Nesterov-accelerated Adaptive Moment Estimation) (Nesterov accelerated gradient).

3. Objective and Methodology

The objective of this study is to analyze and classify the mole images sourced either photographed using a smartphone or a dermoscopic device. Provide access to a

computer-enabled automated, reliable system that can detect melanoma via digital images. The Model using CNN shall be able to process and classify both clinical and dermoscopic images. Analyze images of lesions in a very short time can be a very useful tool in the area of medical diagnosis. The model with end-to-end decision system can detect melanoma patients' lives can be saved at very low cost.

The paper follows CRISP-DM framework. It is a process model which explains approaches in data mining. It is the most widely used model in analytics. It was conceived in 1996 IBM Corporation released a new methodology called Analytics Solutions Unified Method for Data Mining/Predictive Analytics (ASUM-DM). It refines and extends CRISP-DM and has six steps [18]. Further each of the process steps is being discussed in detail from business understanding to data understanding, data preparation, modeling, model evaluation, and deployment feasibility.

4. Business Understanding

Melanoma is a skin growth or tumor produced due to melanocytes transformation into malignant. Melanomas usually occur on the skin. The number of cases of melanoma skin cancer diagnosed worldwide is expected to rise by 18% to 340,271 with the number of deaths increasing 20% to 72,886 by 2040 [19]

Malignant melanoma is the deadliest and speedily increasing skin cancers across the globe. The easy solution would be to get diagnosed early is very much significant to get cured with a simple excision if detected early. The paper objective is to determine that any image source be it clinical or dermoscopic are used to determine benign or malignant. Melanoma cases diagnosed worldwide is expected to rise by 18% to 340,271, the number of deaths increasing 20% to 72,886 by 2040. Close to half a million (466,914) people are expected to be diagnosed with melanoma skin cancer an increase of 62% against 2018 data while 105,904 are expected to die from this deadly skin cancer disease which will be an increase of 74%.

Many studies conducted have used either dermoscopic or clinical images, very minimal studies have been done using both the images together. An inclusive model that can process any mole image and classify as melanoma or benign. Medical practitioners and patients need an easy method at a faster rate in identifying the melanoma and stop the disease spreading further. Need to detect early and classify a normal mole to evolving Melanoma. Highly-trained specialists are required to accurately diagnose Melanoma early which is a very big challenge due to the shortage of experts. Melanoma is more dangerous and has increased over the last decade and early detection of a mole becoming cutaneous melanoma will help reduce mortality rates. The prevalence rate is the proportion of people in the population who have a specific disease or attribute at a specific time or within a specific period (CDC Centers for Disease Control and Prevention 2019). In the United States fifth, most common cancer among men and women is melanoma. White people are more impacted with melanoma than black people which is 20 times more than later. Most women are diagnosed with melanoma much before

the age of 50 however the average age of diagnosis is 65. The development of melanoma occurs when people grow older which is a very common phenomenon. This is also seen younger population who are 30 plus age. Melanoma is the common cancer diagnosed among young adults and older people, mainly in women. Around 2400 cases estimated in 2020 are projected to be diagnosed in the age group of 15 to 29. Skin cancer cases including melanoma have been progressively increasing for several decades. The number of melanoma diagnoses among persons in their 30s decreased somewhat for males and stayed stable for women. Increased sun protection practices and a decline in indoor tanning are probably contributing factors to the decline of melanoma among younger people. Melanoma makes for about 1% of all skin cancer diagnoses in the US. But out of all skin cancer disorders, melanoma is the one that claims the most lives. In the United States, it is anticipated that 7,650 deaths from melanoma (5,080 males and 2,570 women) will take place. But thanks to early detection and treatment, the number of melanoma deaths fell by about 4% annually from 2015 to 2019.

5 Data Understanding and Data Preparation

The datasets are digital photos taken in 2018 and 2019 from a pool of consecutive lesions samples taken from the ISIC. These photographs were captured using digital cameras in a variety of resolutions while operating in nonpolarizing or polarizing modes. Images with poor image quality, ambiguity, or clarity were not included in the dataset. Figure No.3 shows various examples of melanoma photos for classification. The images are manually evaluated and classified as either benign skin lesions or melanoma.



Fig. 3. sample Melanoma and Nevus/ Benign Images (ISIC Archive, 2019) [2]

Images were labelled as benign, naevus, and Melanoma from below sites were used from [3], [2]. 170 images were put into the dataset relying upon their analysis label which has been extracted from the metadata of the pictures. 70 images of melanoma and 100 images labeled as nevus and benign are used in this study. 170 images are non-dermoscopic melanoma and out of that 100 are nevi. The image dimensions range from

201 x 257 to 3177 x 1333 pixels. The dataset has been prearranged into 2 classes containing malignant melanoma Images and the other nevus images. The images from ISIC and from the Med-node archive have been chosen randomly and clubbed for the training, test, and validation.

When transforming images, image augmentation is a crucial technique used that may produce numerous transformed copies of the same old image. Depending on the procedures used for picture augmentation, such as shifting, rotating, flipping, etc., each image copy differs from the other images in some ways. This technique is frequently used for creating deep learning models because applying this image augmentation in small amounts of variations on the original image does not deviate from its target class but only offers another new perspective of capturing the real object practically in day-to-day clinical life.

Images of a nevus with a raised mole with different colors of tan and brown were included. The shapes of the images are oval, round, dome-shaped were part of the data set. The images were largely free from hair. The ISIC data set of benign moles was in a pointed and round shape with bluish color in the background. Malignant melanomas were a combined data set from ISIC and Mednode in equal numbers. The idea was to include the data set variation of two different sources and derive the model.

By ensuring that no identical image is ever used twice during training, the image data generator will go through the image data and randomly change each unique image before it is provided to the model. Rotations, shears, flips, and zooms are just a few of the transformations that can be set when the data generator is instantiated as parameters. This transformation helps to avoid the model from learning noise in the data, such as where features are placed in the image, and makes the model more robust as it trains on slightly distorted images.

One another main obstacles is the big size of the images. The input feature dimension is 1760 * 1470 and the Med-node image dimensions range from 201 * 257 to 3177 * 1333 pixels. This feature size will be very big for computation to process and push to the neural network especially CNN as it also depends on the number of hidden units. The images have three RGB (Red, Green, and Blue) channels, but because of their great computational capacity, they can only be read as a single channel. The data set's image extent is very large in both dimensions of width and height. For instance, a photograph with a width of 1760 and a height of 1470 is highly difficult to process and requires more computing power to register several pictures, which is time-consuming and wasteful of resources. The photographs must be scaled as a result of the aforementioned factors so that the machine can process the images using less memory and graphical processing resources. The approach is defined to address these two issues while reading the photos, in such a way that just one-color channel is retained. Grayscale images are generated from original images for easy process.

There are three layers present in the suggested system. The input layer, which is the initial layer, here the data sets for training are placed. Information from the input layer is gathered that provides by adding weight before moving on to hidden levels. While the patterns are identified, the hidden layer's neurons extract the data's features from it. Using the patterns as foundation right classes are chosen by output layers. As last step binary classification is used, to select classes 1 and 0. Class 0 in this study denotes a benign nevus or mole, whereas class 1 denotes a malignant melanoma with cancerous cells.

Each of the preprocessed images is saved along with their classes. From the dataset, benign and malignant images are taken for further processing. Images are discarded if they are not labeled. At last, the images recorded are fed to CNN. The CNN feature that allows you to reduce the size of the image is important and practical. By choosing a stride of 2, for example, you can confuse the image by taking into account both the horizontal and vertical orientations separately.

Image size is reduced to speed up computation, pooling layers are frequently utilized. Convolutions and pulls are then applied to extract more complicated features. After features flattened to single layer images are fed to fully connected neural network of the model, The intended outcome, which is either benign or cancerous, is then discovered after using the SoftMax.

6 Modeling

The pre-processing model in this study involves merely normalizing the photos, which is benign. The photos are scaled here in this step. Before processing the photos, the data must be multiplied by the rescale factor. The proposed model would struggle to process the original images' RGB coefficients, which range from 0 to 255, at a standard learning rate, thus the values are scaled to be between 0 and 1, or 1/255, instead. In this study, the proposed CNN model has the first layer the convolutional (Conv2D) layer which is like a set of learnable filters opted for 32, 6x6 filters for the two first conv2D layers. Each filter transforms a part of the image (defined by the kernel size) using the kernel filter. The kernel filter matrix is applied to the whole image. Filters can be seen as a transformation of the image. From these altered images, CNN can pick out elements that are valuable everywhere (feature maps).

The pooling (MaxPool2D) layer of CNN is the second crucial layer. This layer merely serves as a down sampling filter, selecting the maximal value after examining the two nearby pixels. These are employed to lower computational expenses and, to a lesser extent, to lower overfitting. After the first two layers followed with Max pool size 2x2 combining convolutional and pooling layers, CNN is able to combine local features and learn more global features of the image.

Dropout is a regularization technique in which, for each training sample, a portion of the layer's nodes are randomly disregarded (their weights are assigned to zero). As a result, a piece of the network is dropped at random, forcing the network to acquire features in a distributed manner. Additionally, this method enhances generalization and lessens overfitting. Dropout in the suggested model is set to 0.3.

'relu' is the rectifier (activation function max (2,2)). The activation of rectifier function will add non-linearity in the network. Final feature maps are converged into single ID vector by using the Flatten layer. In order to employ fully connected layers after several convolutional/maxpool layers, this flattening step is required. It incorporates every local feature discovered in the earlier convolutional layers. Ultimately fully-connected (Dense) layer is used as an ANN classifier. Adam optimizer provides better results. This algorithm is an extension of stochastic gradient descent adopted for deep learning applications.

7 Model Evaluation

The images labeled as "Naevus " and "malignant" were used. The sourced dataset has been organized into 2 classes one with Malignant Melanoma Images and the other Naevus Images with 70/30 for train and validation.

According to the model summary in this paper, the first layer has 3488 parameters. From the above model, the summary understands that the output of each layer of Conv2D and MaxPooling2D layer is a 3D tensor of shape (height, width, channels). The dimension's width and height would shrink as learning goes deeper in the network. The first argument 32 controls the number of output channels for each Conv2D layer. The conv layers are employed to reduce the number of parameters and find local patterns.

Flatten has been employed to connect conv to dense. Dropout 0.3 has been used to avoid overfitting. A dense layer has been employed after conv layers; dense layer helps in classifying the extracted features provided by conv layers. The proposed CNN model has the first layer the convolutional (Conv2D) layer which is like a set of learnable filters, the first two conv2d layers has 32, 6 * 6 filters. Using the kernel filter, each filter alters a specific area of the image. The entire image is subjected to the kernel filter matrix.

Filters can be thought of as a picture alteration. From these transformed photographs, CNN can pick out elements that are valuable everywhere (feature maps). The pooling (MaxPool2D) layer of CNN is the second crucial layer and serves as down sampling filter, choosing the maximum value from the two nearby pixels. These are employed to lower computing costs and may, to a certain extent, lower overfitting.

The Model has run for 60 epochs with training loss at 0.177 and accuracy at 0.94. The model is able to learn until the 60th epoch with validation loss reducing from 0.45 to 0.38 and Validation accuracy at 0.88. This proposed CNN model has better performance even after combined two data sets from ISIC and Med-node. From the literature review, it is learned that many studies have either used one of the datasets while training the model. This model can perform better even with the images having a small mole, large moles, and raised moles with different colors of tan and brown moles.

9.1 Model Performance

The model performance in Fig. 4. has achieved an accuracy of 94 % with training loss at 17.6%, The Validation loss is at 38% for the 60th Epoch and has been decreasing meanwhile the Validation accuracy is increasing which is a good indication that the model is still learning.

Since the validation loss is at 38% the confusion matrix as depicted in Fig. 5. has very less false positives which are labeled as melanoma instead of nevus. However, the model is able to detect the true positive better. The model also is a better type II error the false negative rate is also low.

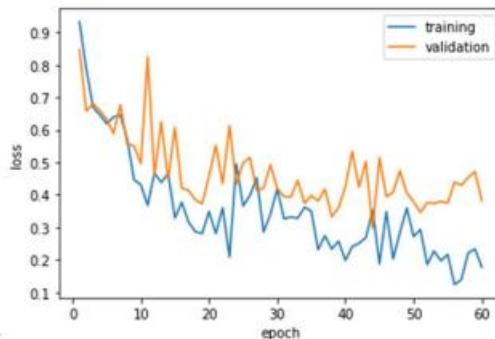


Fig. 4. Training _Validation Plot

Other Metrics Equations and Results

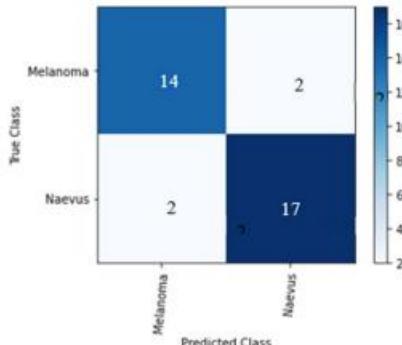
$$\text{Sensitivity} = \text{TP}/(\text{TP}+\text{FN}) \quad 14/(14+2) = 0.87$$

$$\text{Specificity} = \text{TN}/(\text{TN}+\text{FP}) \quad 17/(17+2) = 0.89$$

$$\text{Precision} = \text{TP}/(\text{TP}+\text{FP}) \quad 14 / (14+2) = 0.87$$

$$\text{Negative Predictive Value} = \text{TN}/(\text{TN}+\text{FN}) \quad 17/(17+2) = 0.89$$

$$\text{Accuracy} = \text{TP}+\text{TN}/(\text{TP}+\text{TN}+\text{FP}+\text{FN}) \quad 14+17/(14+17+2+2) = 0.88$$

**Fig. 5.** Confusion Matrix

8 Deployment

The data pipeline appears to arrange the deployment for the future as the business requirement is to create a front-end API as an application. The Complete deployment is not the scope of this project study however have considered the below deployments as a reference for future work. The goal of this stage is to actualize end-to-end applications in which images are taken from smartphones or digital cameras and appropriately classified after the images are run through the preprocessing data generator layer and further fed through the model to detect Melanoma via a Flask API displayed in the UI / dashboard. One of the deployment- Overview of Fully Automated Approach for Early Detection of Pigmented Skin Lesion Diagnosis Using ABCD [20].

Dermatologists all over the world use ABCD as the primary tool for diagnosis while patients use it as a self-examination tool and as a common reference for various skin cancer diagnosis models. This ABCD model is made up of the four main warning signs that can be detected visually and more accurately identified by the computer-embedded deep learning modeled automated system to diagnose melanoma. The features will then be detected using the ABCD rule based on the image area identified during the pre-processing and segmentation.

9 Analysis and Results

The proposed CNN model performance on both Clinical and dermoscopic images has achieved an accuracy of 94 % with training loss at 17.6%, the validation loss is at 38% for the 60th Epoch and has been decreasing meanwhile the validation accuracy is increasing which is a good indication that the model is still learning.

Since the validation loss is at 38% as per the confusion matrix has very less false positives which are labeled as melanoma instead of nevus. However, the model is able to detect the true positive better. The model also is a better type II error the false negative rate is also low.

Overall, the model is able to provide an accuracy of 0.94 which is the best among the studies done on melanoma detection particularly using images from two different data sets from ISIC and Med-node.

Comparing the results from literature review and from the current study are depicted in Table 1. the results from the current study are at par however the improvements have to be made in accuracy and also in classifying right class.

Table 1. Results Summary

Results Tabulation	Specificity	Sensitivity	Precision	Negative Predictive Value	Model Accuracy
Results from this Study	0.89	0.87	0.87	0.89	0.88
Results from Literature Review	0.89	0.894		0.93	0.91

10. Conclusions and Future Scope

Skin cancer is a health problem that has caused concern on a global scale, and early detection of the disease is greatly aided by a reliable automatic melanoma decision system. The deep convolutional neural network that can be utilized for skin cancer classification has inspired the suggested Sequential CNN model. The analysis's findings demonstrate that the new model is more effective than the evaluated studies and pre-trained classification models. The overall ACC for Sequential CNN is 94%. This investigation strongly suggests using AI to identify the deadliest type of cancer since the current proposed model is good reliable in predicting the precise classification with a high true positive rate. We can speed up processing by employing images that are 128 by 128 pixels in size, have three channels, and an inference time of about 0.1 seconds per image. As a result, the suggested technique can perform even better on substantial and evenly distributed skin cancer datasets. Currently, in this study we have analyzed only malignant and benign moles in the next study would like to include all types of melanomas and grade them with severity levels including data from Asian countries. Currently, the data used is from western countries [21]. Further would like to deploy end to end model starting from capturing images in digital cameras and a UI to process and produce the results of detection within minutes with higher accuracy.

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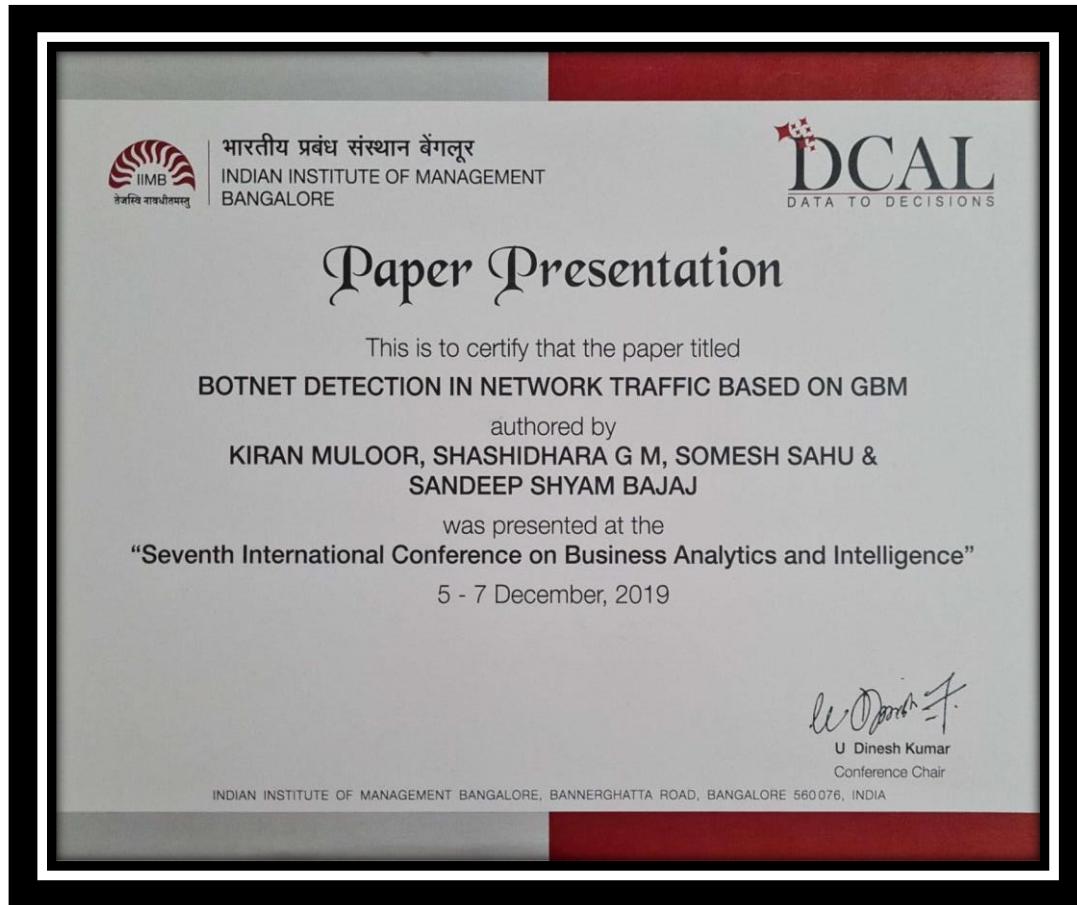


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