Convolution-Attention Approach for Detecting and Diagnosing of Skin Cancer at An Early Stage

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Abstract

Over the years, diagnostic research work on cancer has continued to increase. In skin cancer, a clear way to know is from apparent skin lesions. The area of the skin becomes darker and scaly. The issues lie in the boundary and edge of these lesions. Some parts of the skin affected might not readily show the signs of skin cancer. To accurately detect the extent of the skin cancer from the lesion boundary remains a difficult task. Precisely knowing the border cut off could mean the difference between accurate and inaccurate treatments. Traditional methods of skin cancer classification require a large amount of such strictly labeled data for training classifiers but the SVM classifier doesn't perform well when we have a large dataset since the necessary training time is longer. Another major limitation of the study is that, the conventional CNN used in the existing study treats all skin cancer features from the image equally, resulting in slow learning and less accuracy. Also, as stated in the existing study, the model was not tested with different epochs, batch sizes, classifiers, and optimizers which resulted in the low accuracy recorded in the study. To address these issues, in this research, we proposed an attention-based convolutional neural network for skin cancer detection. The proposed attention model can focus on vital features of the skin cancer datasets while filtering out a large amount of background noise signals. Based on the literature, this is a more efficient approach with better accuracy. Thus, the main objective of the study is to improve the classification accuracy using an improved deep convolution attention model tested with different epochs, batch sizes, and optimizers. Experimental result in MATLAB 2021a shows that the proposed model attains the best accuracy of (92.51%), precision of (90.76%), F-1 of (93.96%), sensitivity of (96.05%) and specificity of (54.76%). Hence, the proposed system achieved the superior classification accuracy of 92.51%compare to the other *classical CNN approaches (DenseNet-201 + SVM, MobileNet + SVM and ResNet-50 + SVM) which achieved accuracy of 86.23%, 85.63% and 85.63 respectively.*

***Keywords**: Malignant, Convolutional Neural Network, and Support Vector Machine*

Introduction

As of 2018, the total number of cancer cases in the world totaled eighteen million, one hundred thousand (18, 100, 000) people. The total number of deaths in the same year was nine million, six hundred thousand (9, 600, 000) people(Vicini, Landrigan, & Straif, 2022). The most common cancer cases include breast, cervix uteri, colorectal, leukemia, liver, non-Hodgkin lymphoma, ovary, prostate, stomach, and brain. Some of the factors that cause cancer include tobacco, alcohol, infections, obesity, ultraviolet rays, and occupational risk(Danaei *et al*., 2005).

Cancer is, commonly, seen as a singular disease, but in fact, it is a group of diseases. These diseases when they inhabit a part of the human body have an abnormal cell growth rate, and could potentially spread to other parts of the body, a concept known as metastasis, if not diagnosed and treated on time properly. There are over one hundred (100) known types of cancer that, actively, affect the human body(Hossen *et al*., 2019).

Skin cancer ranks as one of the deadliest forms of cancer. Skin cancer is a severe disorder of the skin that is brought about by the growth of skin cells in an atypical and unrestrained way (Thurlings *et al.*, 2017). This leads to the atypical cell growth rate which is caused by damaged DNA molecules that occupy these cells. Basal Cell Carcinoma, Squamous Cell Carcinoma, and Malignant Melanoma are the most common types of skin cancer, with melanoma being the commonest and deadliest, accounting for more than ninety thousand deaths in 2015.

The diagnosis of cancer has improved over the years, but it remains difficult. The difficulty persists mostly in the initial stages of the disease; cancer does not produce symptoms in the initial stages. It is not until the disease progresses in terms of mass does the symptoms begin to show. In most individuals, the symptoms could range from prolonged cough to abnormal bleeding. The traditional diagnosis of cancer is done through blood tests, x-rays, computed Utomography scans, and endoscopy.

To understand how cancer is diagnosed traditionally, National Hospital Abuja, a hospital founded in 1999, diagnoses cancer by firstly, conducting a specimen test from the patient's fluid. This test was sent to the histology department; it takes about a month for the sample to be examined and the patient diagnosed with cancer. The diagnosis is finally sent to the oncologist, who carries out another series of specimen tests, x-rays, blood tests, and food blood count tests to ascertain the severity of the disease.

For cases that include skin cancer, extra diagnostic measures are taken. One of these measures is a biopsy, a procedure where the tissue of the disease is extracted from the patient's body; a painful and tedious process. Going with the case study, two major disadvantages are glaring. First, the time complexity of these procedures will endanger patients who need immediate treatments. Another is the painful way of extracting this tissue, in the case of some of these cancer types especially skin.

A solution to these disadvantages is image processing; a non-invasive diagnostic technique. Image processing (Vocaturo *et al.*,2018) makes it possible to detect and diagnose skin cancer at an early stage without the intrusion of biopsies and excessive blood tests. There is a linear path of image processing. Pre-processing, extraction, and classification are all part of this method.

Numerous automated approach base on machine learning have been proposed in the literature to detect skin cancer. However, most of the classical methods are based on shallow learning algorithms, and the low middle-level semantic features extracted are limited in the description ability, which makes it challenging to further enhance the classification accuracy (Yang et al., 2018). Recently, convolutional neural networks (CNNs) have emerged as a rapidly growing trend in big data analysis, being widely and successfully applied across various fields of computer applications, including sequential data processing, natural language processing, speech recognition, and image classification (Abdel-Hamid et al., 2012). This popularity is due to CNNs' superior performance compared to traditional learning algorithms.

As we stand at the cusp of a paradigm shift towards data-intensive science, machine learning techniques are becoming increasingly vital. In particular, deep learning has proven to be an exceptionally powerful tool in numerous domains. However, there is ongoing debate within the computer vision community about whether to fully embrace deep learning as the key to advancements or to be cautious of its "black-box" nature (Zhu et al., 2017).

Convolutional neural networks (CNNs), a type of neural network used in signal and image processing, are favored for their high accuracy in image processing tasks. CNNs operate based on four main layers (Sharma et al., 2020).

First, the input layer receives all the data collected by dermatologists. This layer processes the data and forwards it to the subsequent layers, specifically the pooling layer. The pooling layer performs operations such as max pooling or min pooling to reduce the dimensionality of the data.

Next, the pooling layer passes the data to the flattening layer, which converts the pooled data into a one-dimensional vector. Finally, the data enters the dense layer, where it is classified into the desired categories, such as benign or malignant.

Recent research shows that the convolution neural network has great advantages in feature extraction and has certain degree of invariance to the operation(Chen *et al.*, 2016).The advancements which have been made in the diagnoses of cancer treatments have evolved over the years. From the traditional methods of diagnoses as stated in the background of study to the use of machine learning models. Although these advancements exist, cancer remains a major problem which humans face.

Therefore, this project aims to develop a skin cancer detection base on CNN model which can classify the skin cancer types and help in early detection. The model will also utilize transfer learning techniques to achieve early convergence.

Statement of the Problem

Over the years, diagnostic research work on cancer continues to increase. In skin cancer, a clear way to know is from apparent skin lesions. The area of the skin becomes darker and scaly. The issues lie in the boundary and edge of these lesions. Some parts of the skin affected might not readily show the signs of skin cancer. To accurately detect the extent of the skin cancer from the lesion boundary remains a difficult task. Precisely knowing the border cutoff could mean the difference between accurate and inaccurate treatments.

The existing study of (Keerthana *et al*., 2023) analyzes skin cancer images and provides solutions based on image processing and hybrid CNN+SVM algorithms. The model attained the highest accuracy of 88.02%.However; Traditional methods of skin cancer classification require a large amount of such strictly labeled data for training classifiers but the SVM classifier doesn't perform well when we have large data set because the required training time is higher. Another major limitation of the study is that, the conventional CNN used in the existing study treat all skin cancer features from the image equally, resulting to slow learning and less accuracy. Also, as state in the existing study, the model was not tested with different epochs, batch sizes, classifiers, and optimizers which resulted to the low accuracy recorded in the study.

To address these issues, in this research, we present an attention based convolutional neural network for skin cancer detection. The proposed attention model can focus on vital features of the skin cancer datasets while filtering out a large amount of background noise signals. This is more efficient approach with better accuracy (Wang *et al*.,2019).Hence, our main objective of the study is to proposed to improve the classification accuracy using an improve deep convolution attention model tested with different epochs, batch sizes, classifiers, and optimizers.

Aim and Objectives of the Study

This research aim to improve on the study of (Keerthana *et al.*, 2023) using an improved deep convolutional neural network algorithm. The objectives are;

i. To design an improved Deep Convolutional attention neural network model for early detection of skin cancer.
ii. To train and test the proposed model with different epochs, batch sizes, classifiers, (dataset) and optimizers for improve performance.
iii. To evaluate the efficiency of the proposed method against the existing method in terms of accuracy, sensitivity, precision and specificity.

Conceptual review

There remain so many algorithms in both supervised and unsupervised learning classifiers. However, the benchmark paper uses the CNN from supervise machine learning and SVM from unsupervised machine learning. As a result of the CNN and SVM algorithm's wide historical usage in skin cancer detection. The overview of the fundamental concept focuses on the application of convolutional neural network and support vector machines.

Convolutional Neural Network (CNN)

CNNs where widely applied in various computer application successfully including sequential data. Convolutional Neural Networks mainly focus in learning features that are abstract; this is achieved by stacking and alternating pooling layers and convolution layers respectively. These convolutional kernels, which form the convolution layers in CNN, convolve raw input data with multiple local filters, producing translation-invariant local features. Along with the subsequent pooling layers, they extract features and generate a fixed-length representation over sliding windows of the raw input data, following several rules including average pooling, max pooling, and other parameters accordingly. The CNN is composed of a series of layers, where each layer defines a specific computation as shown in Figure 2.1 these parts are: convolution layers, pooling layers, and fully connected layers. From Figure 2.1 below, the convolution layers are the foremost layer in the CNN network.

The input image maps are convolved with learnable kernels and are subsequently put through the activation function to form the output feature maps. The learning and working process of CNN can be summarized into two stages: (a) networking training and (b) feature extraction and classification. There are two parts for the first stage: a forward part and a backward part. In the forward part, The input image maps are convolved with learnable kernels and subsequently passed through the activation function to form the output feature maps. The learning and working process of CNN can be summarized into two stages: (a) network training and (b) feature extraction and classification.

In the first stage, there are two parts: a forward part and a backward part. In the forward part, the input images are fed through the network to obtain an abstract representation, which is used to compute the loss cost with respect to the given ground truth labels. Based on the loss cost, the backward part computes the gradients of each parameter of the network. Then, all the parameters are updated in response to the gradients in preparation for the next forward computation cycle.

After sufficient iterations of training, in the second stage, the trained network can be used to extract deep features and classify unknown images. Figure 2.1 shows the Convolutional Neural Network framework used for satellite classification.

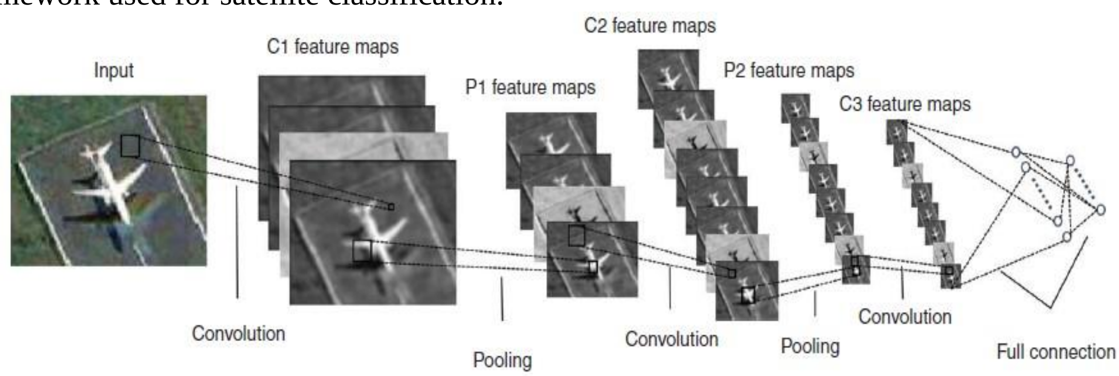

Figure 2.1 Architecture of The Convolutional Neural Networks Framework used for RS Image Classification (Fu'adah, *et al*., 2020)

Researchers including(Esteva *et al.,* 2017) have all confirmed that Convolutional Neural Network is a part of unsupervised learning classifier is an efficient algorithm for skin cancer detection. (Esteva *et al.,* 2017) research was on the classification of skin cancer detection using deep neural network on a dermatologist-level. They established that automated imagery classification of skin lesions was a tedious task, and argued that deep convolutional neural network high potential for tasks pertaining fine-grain objects. They trained the CNN on a dataset of 129, 450 images consisting of different diseases. After the performance was tested, they concluded that CNN performed highly and was on the same level with even human experts.

In Brinker *et al.,* (2018) conducted a systematic review on skin cancer classification using CNN. They established that the success of detecting skin cancer had been dependent on dermatologists. Maron, also researched on comparing the performances of dermatologists and the convolutional neural network. The problem was that dermatologists rarely surpassed a sensitivity level of 80%. They conducted a search, which showed that researchers including (Esteva *et al.*, 2017) have made experiments that showed the CNN was outperforming dermatologists in the area of sensitivity. It's been confirmed that the average sensitivity of CNN lies at 98.8% while the average dermatologists' sensitivity was 56.6%.

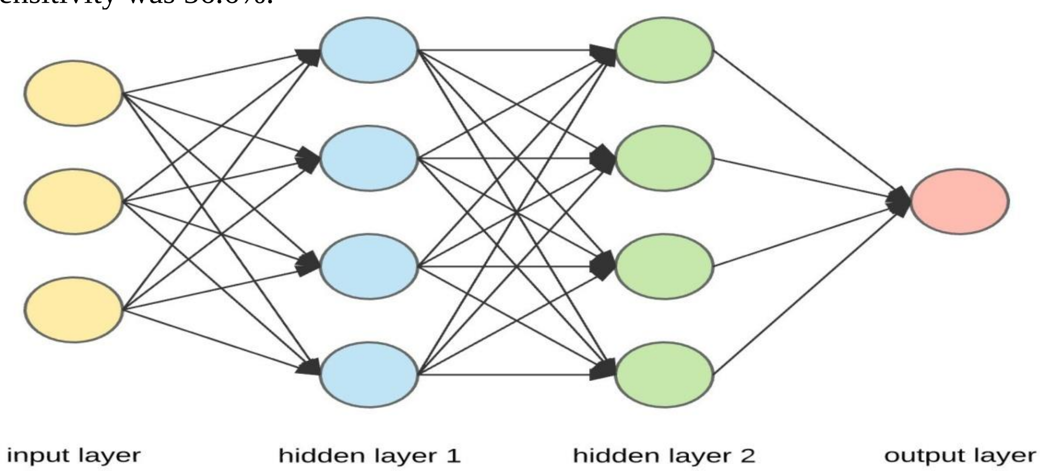

Figure 2.2: Convolution neural network (Zhang et al., 2020).

Support Vector Machine (SVM)

The foundations of Support Vector Machines (SVM) have been developed by (Cherkassky and Ma, 2004), and since then it gained popularity due to many attractive features, and promising empirical performance. Training SVM is a quadratic optimization problem. Support Vector Machines (SVMs) construct the decision surface in a higher-dimensional space by mapping the input signals into that space using nonlinear mapping. For two-class problem, assuming optimal hyper plane in higher dimensional space is generated, the classification decision of an unknown signal X will be made based on kernel function. The kernel function enables the operations to be performed in the input space rather than in the higher-dimensional space. Choosing proper kernel function is dependent on the type of the problem and the given data. According to (Übeyli, 2007) optimal results for SVM were achieved using RBF kernel function (Eleyan, 2012).

On the other hand, Li *et al.* (2020) have proven that the Support Vector Machine, a supervised learning classifier, is usually chosen for its accuracy, high-dimensional and large datasets capabilities. Also, Huang *et al*. (2018) argues that by using SVM in an application, it will go on improve lives. SVM makes it possible to detect diseases at an early stage, with an average sensitivity of 95.7% and an accuracy of 96.9%. similarly, (Murugan *et al*.,2019) compared the detection of skin cancer using SVM, Random Forest, and KNN classifiers. The result showed that the SVM classifier, as regards to skin lesion classification, provided better results.

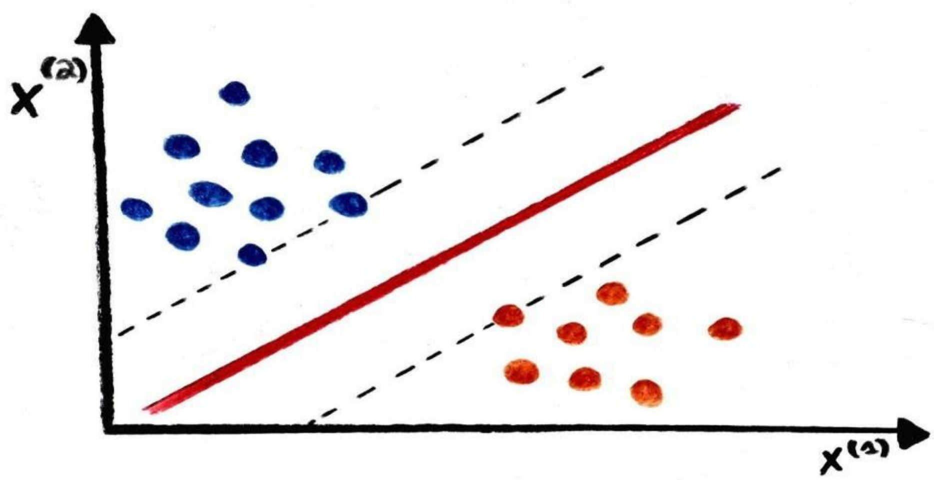

Figure 2.3: Support vector machines (Shavers *et al*., 2006)

The above arguments prove why researchers uses convolutional neural network and support vector machines for skin cancer classification. We present the general review of related work in the next subsection.

Empirical Review

Various methods base on SVM and CNN have been presented in the literature for the classification of skin cancer. For example, Farooq *et al*, (2016) proposed an automatic lesion detection system (ALDS) for skin cancer classification using SVM and neural classifiers. The proposed research work concludes that merged approach of watershed and active contour produces better segmented output. However, limited cancerous moles are in an image.

Also, Alquran *et al*, (2017) proposed early detection and diagnosis of skin cancer using SVM classifier. The results show that the achieved classification accuracy is 92.1%. However, the research was limited by high cost of computing.

More so, Taufiq *et al*, (2017) proposed m-skin doctor: a mobile enabled system for early melanoma skin cancer detection using support vector machine. The m-Skin Doctor achieved a sensitivity rate of 80% and a specificity rate of 75%. However, the average time consumed by the application for classifying one image is14938 ms which too large.

Additionally, Mustafa and Kimura, (2018) proposed an SVM-based diagnosis of melanoma using only useful image features. Results show that only six features can be sufficient to detect melanoma. However, the study could not obtain for darker skinned individuals to experiment with. Recently Arora *et al*., (2020) proposed bag of feature and support vector machine based early diagnosis of skin cancer. The proposed method shows the accuracy of 85.7%, sensitivity of 100%, specificity of 60% and training time of 0.8507 s in classifying the lesion. However, the study fails to consider level of mutilation. The accuracy obtained for detecting melanoma using the SVM diagnosis approach is very effective, however, when the datasets is too large, the high computational cost a major drawback of the aforementioned method. Convolutional neural networks (CNNs) are neural networks that learn the relationship between input objects and class labels even on large datasets. Convolutional Neural Networks (CNNs) are commonly employed for image recognition and classification tasks. Numerous CNN-based architectures for skin cancer detection have been documented in the literature. For instance, Esteva et al. (2017) introduced a deep neural network that provides dermatologist-level classification of skin cancer. This CNN performed at a level comparable to all experts tested across both tasks, showcasing its capability to classify skin cancer with competence similar to that of dermatologists. However, the effectiveness of this method is largely limited by the availability of data; it can classify various visual conditions only if there are enough training examples.
Demir *et al*, (2019) proposed an early detection of skin cancer using deep learning architectures: resnet-101 and inception-v3. The ResNet-101 architecture achieved an accuracy rate of 84.09%, while the Inception-v3 architecture attained an accuracy rate of 87.42%. However, if the network is too shallow, the learning might be very inefficient. More so, (Setiawan, 2020) investigate effect of color enhancement on early detection of skin cancer using convolutional neural network. he results indicate that, compared to MSRCR, CLAHE is more effective for color image enhancement in the early detection of skin cancer using CNNs. However, limited number of classes is used in classification.

Fu'adah *et al*., (2020) proposed convolutional neural network (CNN) for automatic skin cancer classification system. Experimental result shows that Adam optimizer provides the best performance with an accuracy value of 99% in identifying the skin lesions from the ISIC dataset into 4 classes. However, the method could not obtain for darker skinned individuals to experiment with.

(Zhang *et al*., 2020) proposed skin cancer diagnosis based on optimized convolutional neural network. The final results demonstrated that the proposed method achieved the highest performance for skin cancer diagnosis. However, limited cancerous moles are in an image. Also, (Nahata and Singh, 2020) uses transfer learning base on CNN model. The best model, namely Inception Resnet achieved an average accuracy of 91%. However, the system treats all cancer features equally which limits the accuracy.

Garg *et a*l.,(2021) proposed decision support system for detection and classification of skin cancer using CNN. The model gave a weighted average Precision of 0.88, a weighted Recall average of 0.74, and a weighted f1-score of 0.77. The transfer learning approach applied using ResNet model yielded an accuracy of 90.51% but still limited by low accuracy.

Similarly, Alizadeh and Mahloojifar, (2021) proposed an automatic skin cancer detection in dermoscopy images by combining convolutional neural networks and texture features. The proposed approach can increase the performance of melanoma detection, compared to previous studies but could not obtain for darker skinned individuals to experiment with.

Subramanian *et al.*, (2021) proposed skin cancer classification using Convolutional neural networks. Final result revealed that that using the Standard CNN method gives the best achievement for the Skin cancer diagnosis. However, limited number of classes is used in classification. In order to compliment one algorithms weakness with another algorithm strength for more efficient result, researchers have combined classical machine learning algorithms like Support vector machine (SVM), k-nearest neighbor (k-NN), and decision tree (DT) with CNNs for classification purposes. For example, (ALEnezi, 2019) proposed Skin cancer detection using pretrained convolutional neural network(AlexNet) and SVM. The system successfully detects 3 different types of skin diseases with an accuracy rate of 100%. However, the system is computationally slow and could not detect all kind of skin disease.

Elngar *et al*., (2021) proposed (CNN-SVM -MAA) system and detect cancer with efficient results. However, the system treats all cancer features equally.Keerthana *et al.*, (2023) analyzes skin cancer images and provides solutions based on image processing and hybrid CNN+SVM algorithms. The model attained the highest accuracy of 88.02%. However, as seen in the literature, traditional methods of skin cancer classification base on CNN and SVM require a large amount of such strictly labeled data for training classifiers but the SVM classifier doesn't perform well when we have large data set because the required training time is higher.

Another major limitation of the study is that, the conventional CNN used in the study treat all skin cancer features from the image equally, resulting to slow learning and less accuracy. Also, as stated by the author, the model was not tested with different epochs, batch sizes, classifiers, and optimizers which resulted to the low accuracy recorded in the study. Tables 2.1 depict the summary of related work by work authors, research title ,methods used, problems addressed and solution proffered.

Method

This outlines the methodological approach employed to develop and evaluate the skin cancer detection model. It describes the dataset used, preprocessing steps, model architecture, training process, and evaluation metrics. Each step was meticulously executed to ensure the model's robustness and accuracy.

Dataset

The dataset used for this study was from the International Symposium on Biomedical Imaging (ISBI) 2016 challenge, which included images for skin lesion analysis. This dataset was chosen for its comprehensive nature and relevance to the task of melanoma detection. It comprised images of skin lesions, categorized into benign and malignant classes, along with corresponding clinical information.

Data Preprocessing

Several preprocessing steps were applied to the dataset to enhance the quality of the images and prepare them for the model. These steps included:

1. **Outlier Removal**: Images with extremely light or dark pixel intensities were identified as outliers and removed from the dataset.
2. **Progressive Resizing**: Images were progressively resized to ensure consistent input dimensions for the model. This involved resizing the images to 300x300 pixels.
3. **Filtering**: Difference of Gaussian (DOG) filtering was applied to enhance the features of the images. The filtered images were further processed to produce enhanced DOG filter images.

Data Augmentation

Data augmentation techniques were employed to artificially increase the size of the dataset and improve the model's generalization ability. The techniques used included random rotations, flips, and zooms. This ensured the model was exposed to a variety of image transformations, enhancing its robustness.

Model Architecture

The model architecture was designed using Convolutional Neural Networks (CNNs), known for their effectiveness in image classification tasks. The architecture included several convolutional layers, followed by pooling layers and fully connected layers. An attention mechanism was incorporated to allow the model to focus on relevant parts of the image.

Convolutional Layers

Convolutional layers were used to extract features from the input images. These layers applied a series of filters to the images to detect edges, textures, and other important features.

Pooling Layers

Pooling layers were used to reduce the spatial dimensions of the feature maps, retaining only the most important information. This helped in reducing the computational complexity of the model.

Fully Connected Layers

Fully connected layers were used to combine the features extracted by the convolutional layers and make the final classification decision. These layers provided a high-level abstraction of the features.

Attention Mechanism

An attention mechanism was incorporated to allow the model to focus on the most relevant parts of the images. This improved the model's ability to correctly identify and classify skin lesions.

Training Process

The model was trained using the AdamW optimizer, which was chosen for its ability to handle sparse gradients and its effectiveness in deep learning applications. The training process involved:

1. **Batch Size and Learning Rate**: The model was trained with varying batch sizes and learning rates. The maximum learning rate was set to 0.0002, and the minimum bound was set to one-tenth of the maximum learning rate.
2. **Epochs**: The model was trained for 10 epochs, with adjustments made to the learning rate based on the one-cycle policy.
3. **Optimizer**: The AdamW optimizer was used to train and optimize the model parameters. It combined the benefits of both Adam and weight decay, ensuring better generalization.

Evaluation Metrics

The model's performance was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and specificity. These metrics provided a comprehensive assessment of the model's ability to correctly classify skin lesions.

1. Accuracy

Accuracy was calculated as the ratio of correctly classified instances to the total number of instances. It provided an overall measure of the model's performance.

2. Precision

Precision measured the ratio of true positive instances to the sum of true positive and false positive instances. It indicated the model's ability to correctly identify positive instances.

3. Recall (Sensitivity)

Recall, or sensitivity, measured the ratio of true positive instances to the sum of true positive and false negative instances. It indicated the model's ability to correctly identify all positive instances.

4. F1-Score

The F1-score was the harmonic mean of precision and recall. It provided a balanced measure of the model's performance, especially in the presence of imbalanced classes.

5. Specificity

Specificity measured the ratio of true negative instances to the sum of true negative and false positive instances. It indicated the model's ability to correctly identify negative instances.

Result and Analysis

This chapter presents the result obtained after simulating the network on MATLAB 2021a. The results are presented in tabular and graphical forms, which are analyzed using standard performance classification evaluation metrics used for computer vision application. The dataset was imported in into the simulation software and fed to model.

Experimental Setup and System Requirement

The experiment was verified on an NVIDIA™ Titan X GPU with 12 GB of memory. The prerequisite for the experiment were

i. CUDA enabled NVIDIA GPU with compute capability 3.2 or higher.
ii. NVIDIA CUDA toolkit and driver.
iii. NVIDIA cuDNN library.
iv. Environment variables for the compilers and libraries.
v. GPU Coder Interface for Deep Learning Libraries support package. To install this support package, we use the Add-On Explorer.

The requires for this includes

i. MATLAB
ii. Deep Learning Toolbox
iii. Image Processing Toolbox
iv. Computer Vision Toolbox
v. Parallel Computing Toolbox
vi. MATLAB Coder
vii. GPU Coder

And finally, the Support Packages includes

i. Deep Learning Toolbox Importer for Caffe Models
ii. MATLAB Support Package for USB Webcams
iii. GPU Coder Interface for Deep Learning Libraries

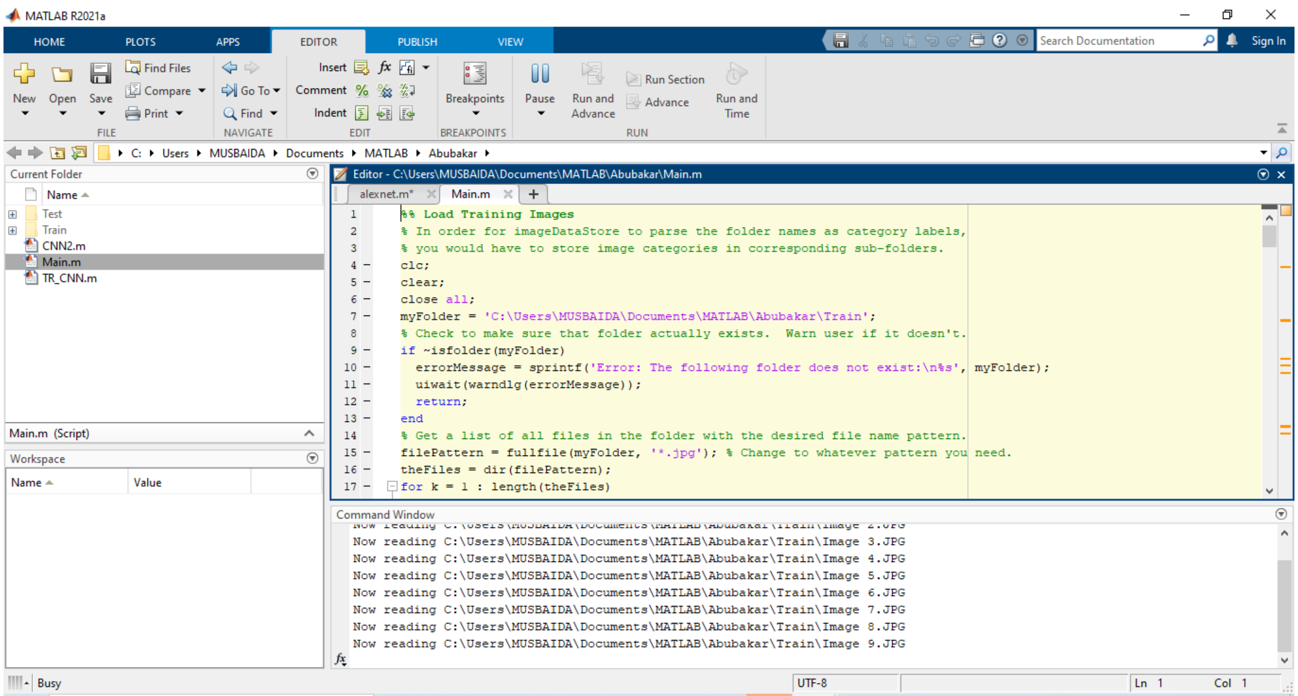

Figure 4.1:MATLAB Simulation Environment

The International Symposium on Biomedical Imaging (ISBI) 2016 did include a challenge related to skin cancer image analysis. The challenge was called the "Skin Lesion Analysis Towards Melanoma Detection" challenge. The ISBI 2016 Skin Lesion Analysis Challenge aimed to promote research in the field of computer-aided diagnosis of melanoma, a type of skin cancer. The challenge provided a dataset for participants to develop and evaluate their algorithms for skin lesion analysis. The dataset typically included images of skin lesions along with corresponding clinical information, such as the diagnosis or certain characteristics of the lesions. Participants were tasked with developing algorithms that could assist in distinguishing between benign and malignant skin lesions.Figure4.2 depict the sample images of the ISBIC dataset. The boxes highlight benign and malignant skin lesions.

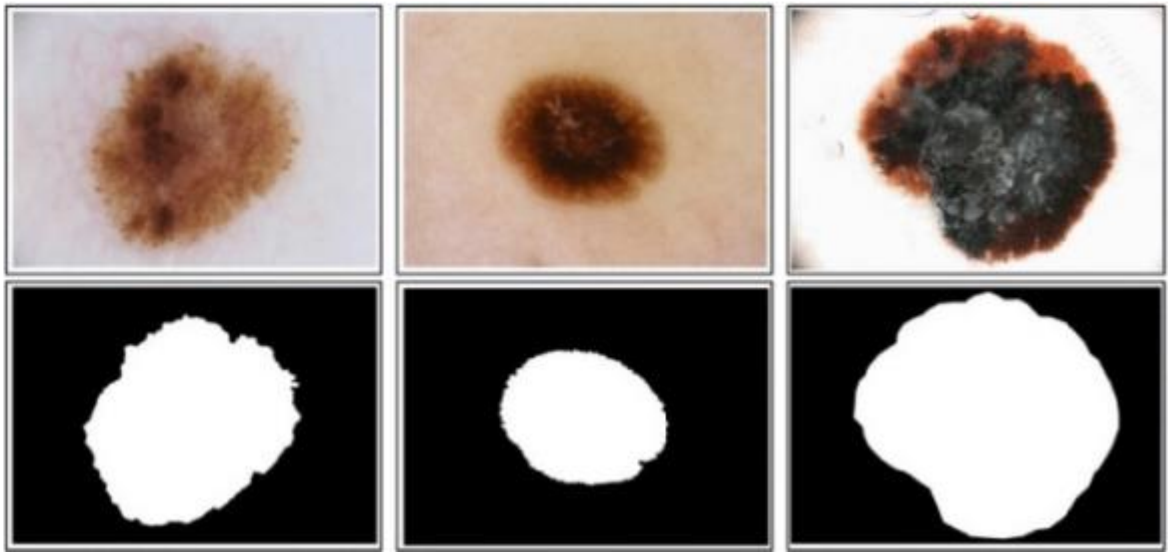

Figure:4.2 the sample images of the ISBIC *dataset*

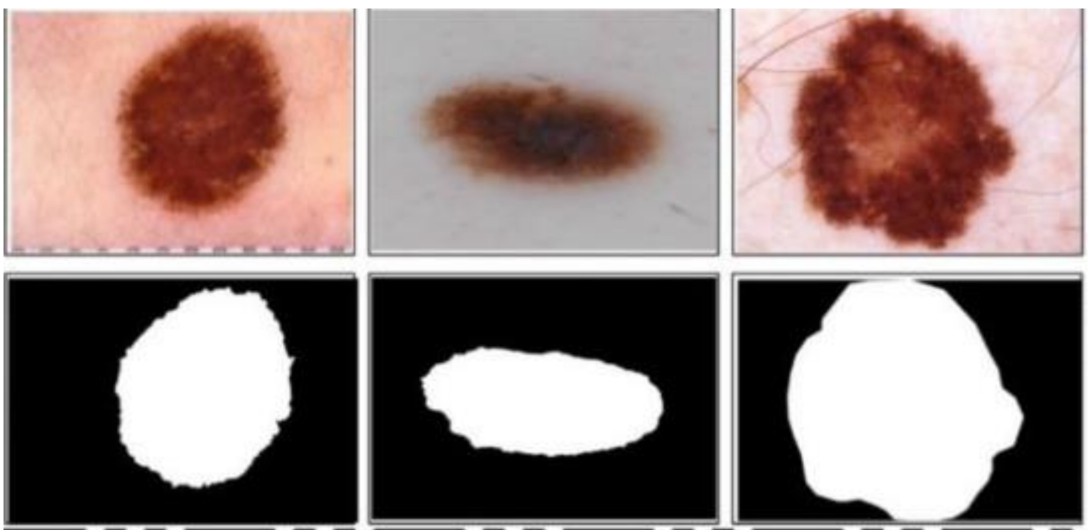

Figure 4.3 the sample images of the ISBIC dataset

The images with either too light or too dark pixel intensities were recognized as outliers and thus removed.

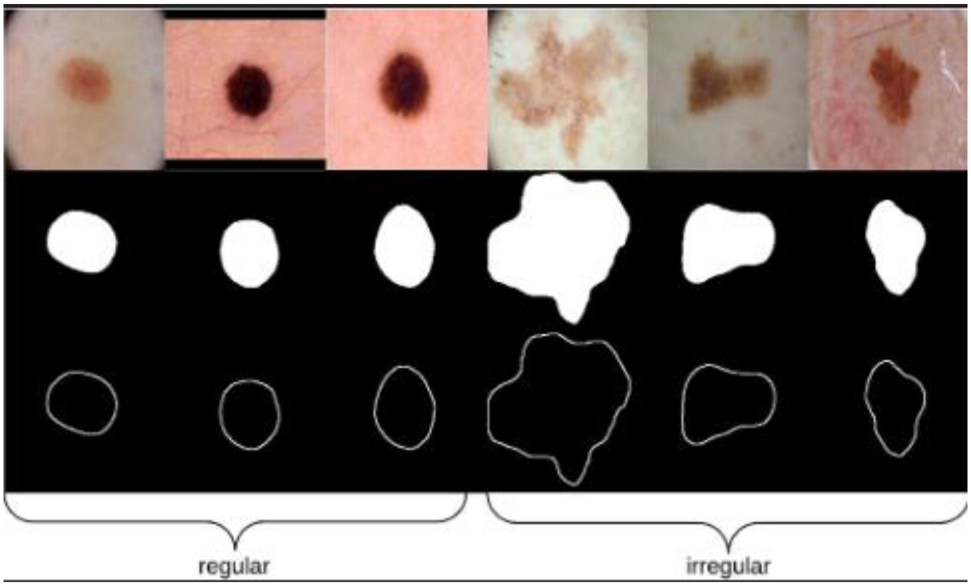

Figure 4.4 the sample images of the ISBIC dataset with regular and irregular ecotecture.

During the experiment, progressive resizing of images was used to train the models. All the models were trained for 10 epochs with variable batch size with the learning rate altered in base on one cycle policy, a maximum learning rate set to 0.0002 and the minimum bound was set to 1/10 of the maximum learning rate. The AdamW was used to train and optimized the parameters of the model. The summary for the parameter settings is presented in Table 3.

Table 4.1: Parameter settings

Parameters	**Settings**
Input Size	[300 300 3]
Mini Batch Size	Varying
Initial Learn Rate	0.0002
penalty threshold	0.7
Warmup Period	1200
l2Regularization	0.0005
Max Epochs	10
Optimisers	AdamW
Verbose Frequency	50

During the experiment, the image was presented into four classes (original image, grey image, DOG filtered image and the enhanced DOG filter image) as shown in Figure 4.5

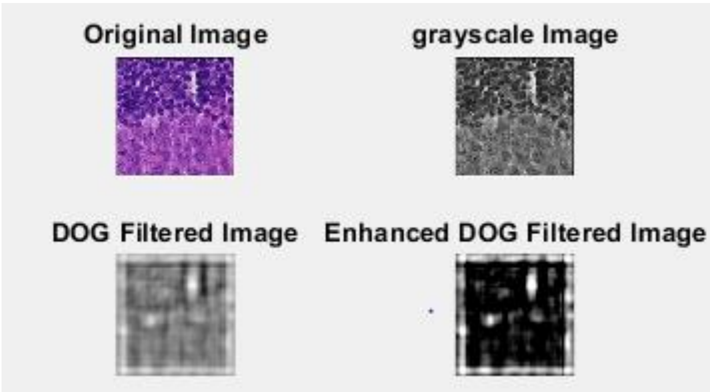

Figure 4.5. Sample preprocess image

To evaluate the model, the Computer Vision System Toolbox™ in MATLAB 2021 provides object detector evaluation functions to measure common metrics such as accuracy, precision and recall rates. However, this research, the accuracy, precision, sensitivity, specificity and F-score metric were used. The better the model is at prediction performance. By analogy, the higher the values of each metric, the better the model is at distinguishing between patients with the cancer and no cancer. The result of the proposed model is presented in the next subsection.

Result

After experiments on dataset, this section presents the detection rate for the proposed model on the cancer datasets as compared to other state of the art techniques. We split the result presentation into two subsections, firstly, we present the general assessment of the proposed model based on varying number of epochs and batch size, and secondly, we compare the classification performance of the proposed study with other state of the art approaches.

Model Evaluation Base on Number of epochs, batch size and optimizers

The number of epochs and batch size are interconnected hyper parameters that play a crucial role in training deep learning models for skin cancer detection. The optimal values depend on the specific dataset, model architecture, and computational resources available, and it's common to experiment and fine-tune these hyper parameters for the best performance. The number of epochs and batch size are crucial hyper parameters that can significantly impact the training process and performance of a deep learning model, including those used for skin cancer detection.

The number of epochs determines how many times the model goes through the entire training dataset. Convergence occurs when the model has learned the patterns in the data, and the training loss stabilizes. Monitoring the validation loss can help identify when further training may not improve performance. The batch size represents the number of samples processed in each iteration. Hence, table 4.2 present the detection rate base on different epochs and batch sizes using adamW optimizers.

Table 4.2 performance of the proposed model base on varying epochs and batch size

No. Epochs	Batch Size	Optimizer	Test Acc (%)	Train Acc (%)	Under fitting rate	Over fitting rate
10	15	AdamW	90.68	54.33	Yes	**No**
15	20	AdamW	91.88	59.22	Yes	**No**
20	25	AdamW	91.29	66.16	Yes	**No**
25	30	AdamW	92.51	92.78	No	**No**
30	35	AdamW	93.32	92.81	No	**No**
35	40	AdamW	94.55	96.77	No	**Marginal Overfit**
40	45	AdamW	94.88	97.34	Overfit	**Overfit**
45	50	AdamW	94.91	98.39	Overfit	**Overfit**

From Table 4.2, it is noticed that too few epochs may result in under fitting, where the model fails to capture the underlying patterns in the data. On the other hand, too many epochs can lead to over fitting, where the model memorizes the training data but does not generalize well to new, unseen data. Hence, the stable and generalized performance was achieved for the case of moderate epochs and batch size of 25, 30 and 30, 35 respectively. Thus, the model attains a better test and training accuracy of 93.32% and 92.81% respectively.

However, with larger values of epochs and batch size, it was notice that the model tends to over fit (see table 4.2). Over fitting in CNN is said to occur when the accuracy of training dataset is greater than testing accuracy, or in other words, when the model is too complex for the problem it is solving. This is a flaw as the model will know the training data well, but when a new data is introduced to it, it will underperform. Hence, the model was most over fit with at large epochs of 40 and 45 respectively. Thus, the model attains a better test and training accuracy of 94.91% and 98.39% respectively.

Form the experiment, it was noticed that larger batch sizes can lead to more stable updates to the model's weights. However, these are often more computationally efficient, especially when using hardware acceleration like GPUs. Thus, smaller batch sizes may promote better generalization, as the model updates its weights more frequently, potentially adapting to different patterns in the data. However, very small batch sizes can lead to noisy updates. Therefore, the choice of batch size should consider memory constraints. Larger batch sizes require more memory, and the model may not fit into memory for very large batches. The choice of batch size can be related to the learning rate. Larger batch sizes often require larger learning rates to prevent convergence issues.

Furthermore, we used other decision support accuracy to evaluate the performance of the model against state-of-the-art approaches.

Performance Comparison with Existing Methods

In this subsection, we evaluate the performance of the developed model using decision support accuracy such as accuracy, precision and sensitivity. This is because accuracy maybe misleading, in some cases, we need to extend the evaluation of a model using other decision support accuracy to ensure the reliability of the model. The accuracy performance metric deals with the correct prediction made by the model and this metric.

On the other hand, precisions provide information about how precise/accurate your model is out of those predicted positives, how many of them actual positives are. Precisions are a good measure to determine when cost of false positives is high. Table 4.3 present the accuracy, precision, F-1, Specificity and sensitivity achieved by the optimal CNN architecture at 25, epochs and batch size 30 respectively.

Table 4.3 performance comparison with existing method base on epoch and batch size

Model	Optimisers	No. Epochs	Batch Size	Accuracy (%)	Precision (%)	F-1 (%)	Specificity (%)	Sensitivity (%)
Proposed Attention CNN	AdamW	25	30	92.51	90.76	93.96	54.76	96.05
DenseNet-201 + SVM	Adam	25	30	86.23	88.16	92.73	33.33	97.81
MobileNet + SVM	Adam	25	30	85.63	87.26	93.20	33.33	97.10
ResNet-50 + SVM	Adam	25	30	85.63	86.93	91.72	33.33	97.08

In Table 4.3, each of the evaluation metrics (accuracy, precision, specificity, sensitivity and F-1) was reported between 0 to 100%, it is quite obvious that the proposed system achieved the best performance in terms of (accuracy, precision, specificity, sensitivity and F-1). This demonstrates the superiority of the proposed model against the other existing algorithms. In the next subsections, we provide a detailed discussion of the results analysis and evaluation based on the standard evaluation metric use in this study. (accuracy, precision, specificity, sensitivity and F-1).

Discussion of Result

Classification Accuracy

This performance metric deal with the correct prediction made by the model. It's important to note that achieving extremely high prediction accuracy in skin cancer detection is often challenging due to the inherent complexity and variability. The goal is typically to prioritize and focus testing efforts on the most likely defect-prone areas using the attention mechanism rather than aiming for perfection. Figure 4.6 depict the performance achieved by the proposed model against the approaches.

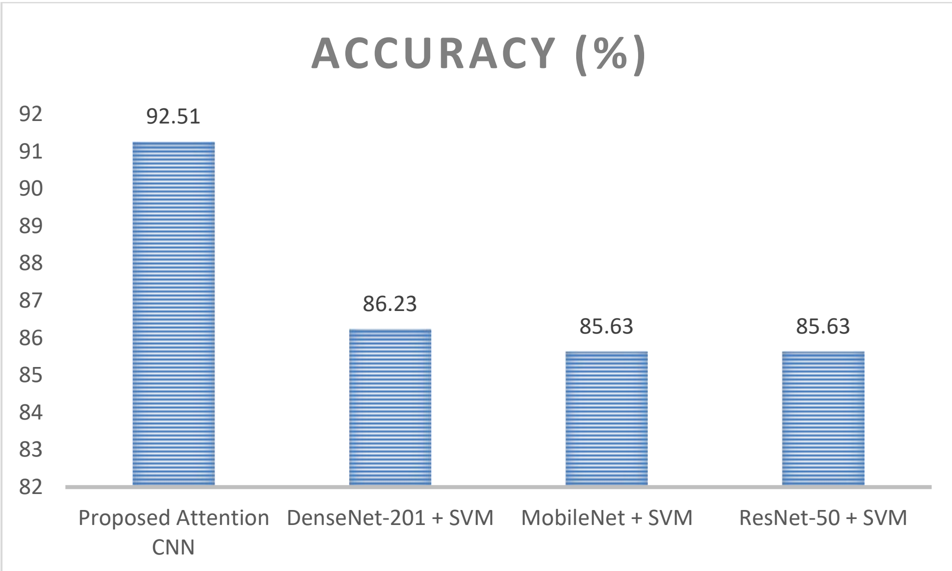

Figure 4.6: Classification accuracy for all methods

In Figure4.6, it is noticed that the proposed system achieved the superior classification accuracy of 92.51%compare to the other classical CNN approaches (DenseNet-201 + SVM, MobileNet + SVM and ResNet-50 + SVM) which achieved accuracy of 86.23%, 85.63% and 85.63 respectively. This suggests that the proposed model predicted the correct instances with higher accuracy compare to the state-of-the-art deep learning method.

Accuracy is a simple and intuitive metric, but it may not always be the best choice for evaluating a model's performance, especially in cases where the classes are imbalanced. In situations where one class dominates the dataset, a model that predicts the majority class for every instance might achieve a high accuracy, even though it's not really performing well. In such cases, other metrics like precision, sensitivity, specificity and F1-score are often used to provide a more comprehensive understanding of a model's performance, particularly when dealing with imbalanced datasets. These metrics consider factors such as false positives, false negatives, and true positives to provide a more nuanced evaluation of a model's abilities. Therefore, the precision was elaborated in the next subsection.

Precision

The accuracy can be misleading in some cases as stated earlier. Precision, F-1, Specificity and sensitivity help us further understand how strong the accuracy shown holds true for a particular problem. Precision is a metric used in machine learning, particularly in the context of binary classification, to measure the accuracy of positive predictions made by a model. It answers the question: "Out of all instances that the model predicted as positive, how many were actually positive?" In other words, precision focuses on the quality of positive predictions. It is the ratio of true positive predictions (correctly predicted positive instances) to the total number of instances predicted as positive (true positives plus false positives). Figure 4.7 depict the performance achieved by the proposed method against the existing method for the precision.

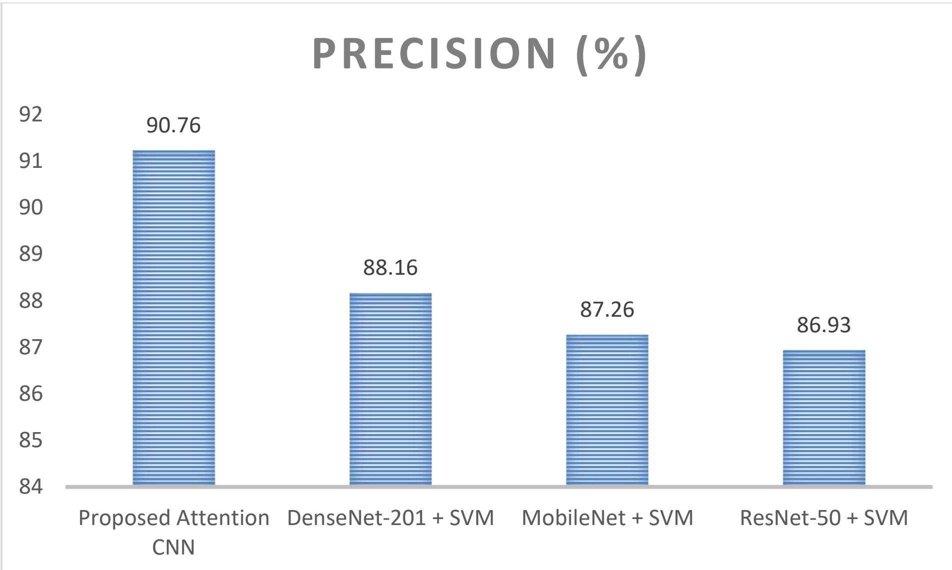

Figure 4.7: Precision for all method

From Figure 4.7 above, it is noticed that the proposed system achieved the superior precision of 90.76%compare to the other classical CNN approaches (DenseNet-201 + SVM, MobileNet + SVM and ResNet-50 + SVM) which achieved accuracy of 88.16%, 87.26% and 86.93 respectively. However, precision doesn't take into account the cases where the model missed positive instances (false negatives), which is where sensitivity comes into play. The choice between sensitivity and precision depends on the specific goals and requirements of a machine learning or classification task. Sensitivity and precision are two key metrics used to evaluate the performance of binary classification models, and they capture different aspects of model behavior.

Sensitivity, also known as recall or true positive rate, measures the proportion of actual positive instances that were correctly identified by the model. It is calculated as Sensitivity = True Positives / (True Positives + False Negatives).Sensitivity is important when the cost of false negatives (misclassifying a positive instance as negative) is high. In medical diagnoses, missing a positive case (e.g., a disease) can have serious consequences. Sensitivity provides insights into a model's ability to capture all relevant positive instances.In medical diagnostics, a model with high sensitivity would be desired to ensure that as many cases of a disease are detected as possible, even if it results in some false positives. Therefore, the sensitivity score is analyzed in the next subsection.

Sensitivity

As stated earlier, the precision and recall help us further understand how strong the accuracy shown holds true for a particular problem. Fig. 4.8 depict the performance achieved by the proposed method against the existing CNN method.

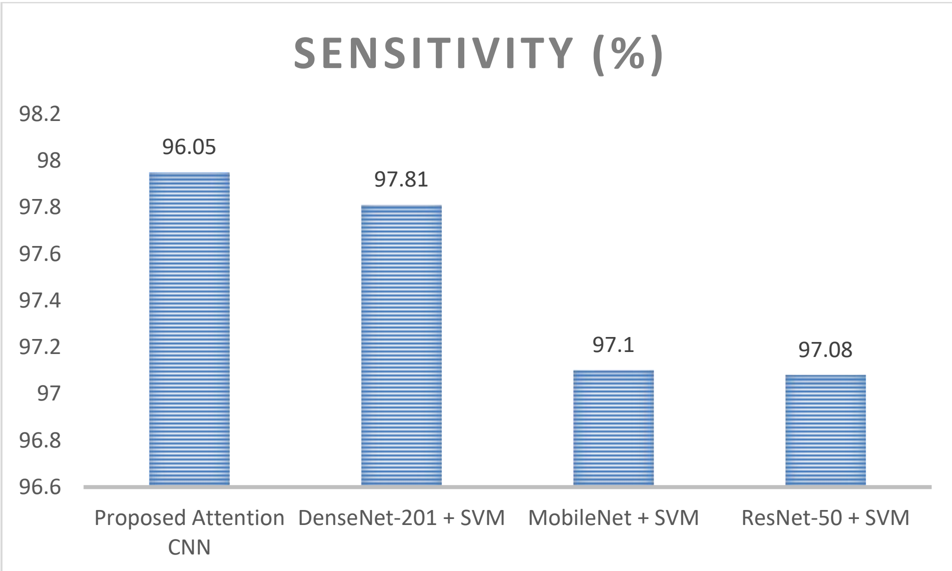

Figure 4.8: Sensitivity for all method

From Figure 4.8 above, it is noticed that the proposed system achieved the superior classification sensitivity of 96.05%compare to the other classical CNN approaches (DenseNet-201 + SVM, MobileNet + SVM and ResNet-50 + SVM) which achieved accuracy of 97.81%, 97.1% and 97.08 respectively. Although, precision and recall are often combined into a single metric called the F1-score, which provides a balance between the two.

F-1

The F-Measure provides a single score that balances both the concerns of precision and recall in one number. In statistical analysis of binary classification, the F1 score (also known as the F-score or F-measure) is a measure of a test's accuracy. It is calculated from the precision and recall of the test. Precision is the number of correctly identified positive results divided by the total number of positive results identified, including those not identified correctly. Recall is the number of correctly identified positive results divided by the total number of samples that should have been identified as positive. In each case a higher value shows how confident the classification accuracy or performance can be relied upon.

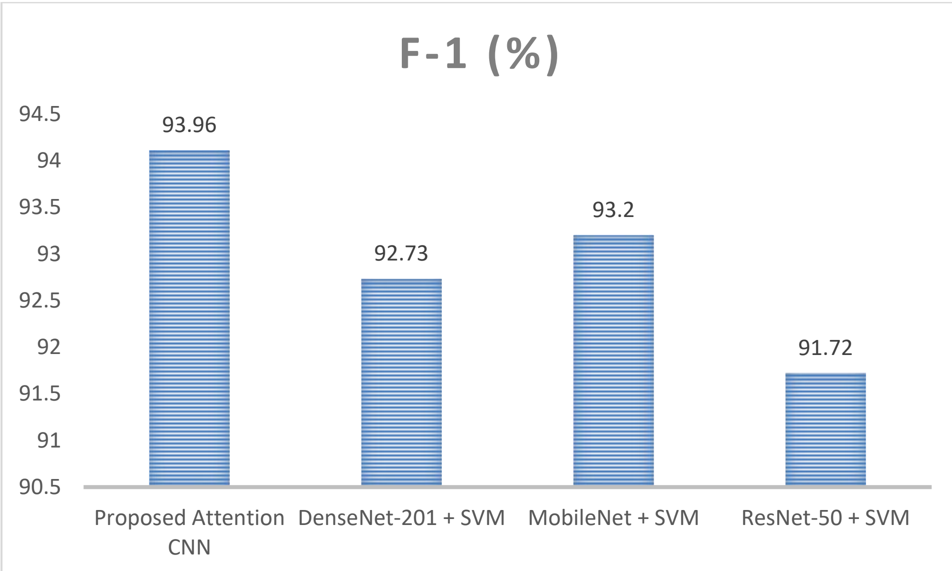

Figure 4.9: F-1 for all methods

From Figure 4.9 above, it is noticed that the proposed system achieved the superior classification F-1 of 93.96 %compare to the other classical CNN approaches (DenseNet-201 + SVM, MobileNet + SVM and ResNet-50 + SVM) which achieved accuracy of 92.73%, 93.2% and 91.72 respectively.

Specificity

Specificity is a key metric in the context of skin cancer prediction using CNNs. It provides insights into the ability of the model to correctly identify individuals without dementia, minimizing false positives. In the context of skin cancer prediction, high specificity indicates that the CNN model is effective in correctly identifying individuals without skin disease. This is crucial for minimizing the risk of false alarms and unnecessary concern for individuals who do not have dementia.

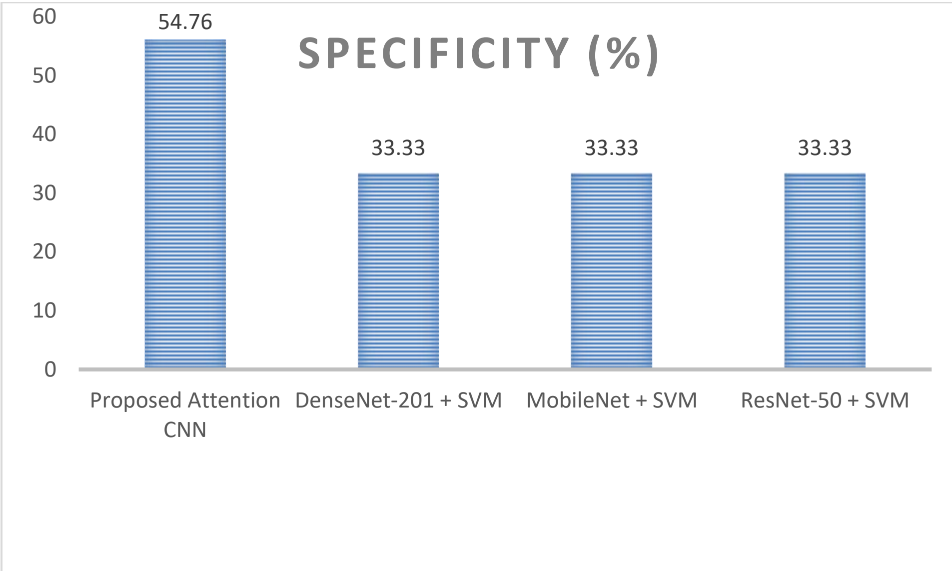

Figure 4.10: Specificity for all methods

From Figure 4.10 above, it is noticed that the proposed system achieved the superior classification Speciificty of 54.76%compare to the other classical CNN approaches (DenseNet-201 + SVM, MobileNet + SVM and ResNet-50 + SVM) which achieved accuracies of 33.33% respectively. thus, we present the overall results in Fig. 11

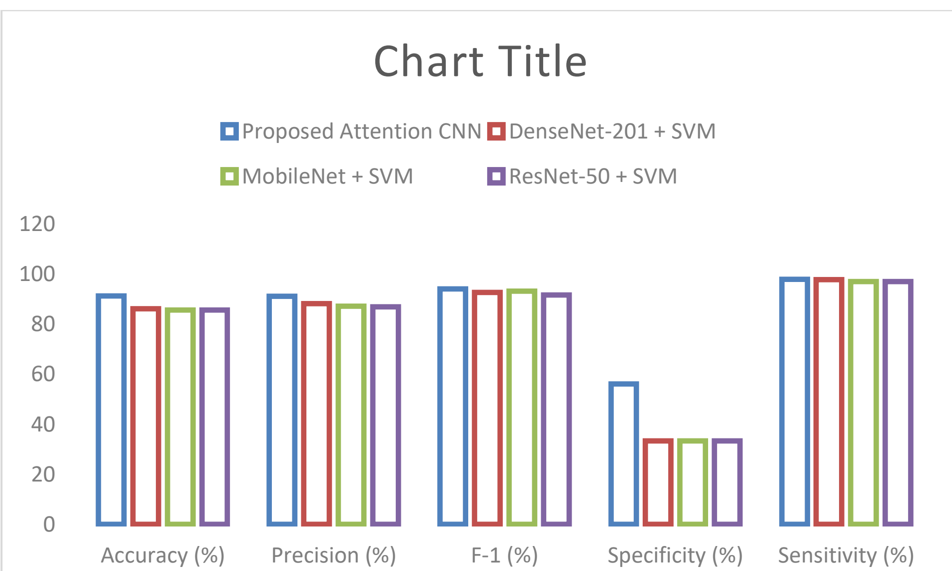

Figure 4.11: Overall Results for all methods

From Figure 4. 11, it was noticed that the proposed model attains the best result in terms of accuracy (92.51%), precision (90.76%), F-1 (93.96%), sensitivity (96.05%) and specificity (54.76%). It was further noticed that specificity score for all the models were low, this may due to the trade-off between sensitivity and specificity. This is a key consideration in binary classification models, and it is influenced by the choice of the classification threshold. Understanding this trade-off is crucial for optimizing a model's performance based on the specific goals and requirements of a given application.

Thus, the result from this study shows that the attention layer that can enhance the performance of Convolutional Neural Network (CNN) for skin cancer detection. The attention layer can enable the CNN focus on vital features of the skin cancer datasets while filtering out a large amount of background noise signals. This is more efficient approach with better accuracy as seen in other literature (Wang *et al*., 2019). Additionally, experimentally, this has shown that AdamW yields better training loss and that the models generalize much better than all the existing models trained with Adam allowing the new version to compete with stochastic gradient descent with momentum (Guan, 2023).

Summary

Cancer remains the leading cause of death worldwide, with breast cancer as the most prominent cause of cancer deaths. The world Health Organization (WHO) Global cancer observatory chat reported that in Nigeria, among the ten most common cancers, breast cancer is the most frequently occurring, and has the highest mortality rate among women (WHO, 2021). Research shows that even the most skilled physicians can detect cancer with at most 79% accuracy, while 91% correct diagnosis is achieved using machine learning techniques.

Skin cancer diagnosis is faced with a lot of difficulties as the pathological images are hard to define, and, distinguishing skin cancer cells from other cells is a very tedious task, even to the most experienced doctors. Furthermore, some very minor regions can be missed. Medical practices have taken another shape today by using technologies power-driven by Artificial intelligence (AI) to huge differences to human health. Convolutional Neural Network is currently the most popular deep learning practice for detecting and classifying images in cancer, bringing along momentous contributions, and having added benefits of scalability and automation when compared to human experts.

To address these issues, in this research, we present an attention based convolutional neural network for skin cancer detection. The proposed attention model can focus on vital features of the skin cancer datasets while filtering out a large amount of background noise signals. This is more efficient approach with better accuracy. Hence, the main objective of the study is to proposed to improve the classification accuracy using an improve deep convolution attention model tested with different epochs and batch sizes.

Conclusion

A deadly and aggressively spreading disease like cancer deserves a consistent approach to its early and accurate detection. This early detection has been proven as the only way to completely cure cancer. This research targets the faults associated with skin cancer screening by introducing the Convolutional attention Mechanism in the screening of skin so that cancerous cells can be detected even at their earliest stages development. Experimental result in MATLAB 2021a shows that the proposed model attains the best accuracy of (92.51%), precision of (90.76%), F-1 of (93.96%), sensitivity of (96.05%) and specificity of (54.76%). Hence, the proposed system achieved the superior classification accuracy of 92.51%compare to the other classical CNN approaches (DenseNet-201 + SVM, MobileNet + SVM and ResNet-50 + SVM) which achieved accuracy of 86.23%, 85.63% and 85.63 respectively. This suggests that the proposed model predicted the correct instances with higher accuracy compare to the state-of-the-art deep learning method. It was further noticed that specificity score for all the models were low, this may due to the tradeoff between sensitivity and specificity. This has proven the technical validity of the proposed approach to detect skin cancer with high decision support accuracies.

Limitations of the Study

The low trade-off between sensitivity and specificity is a key consideration in binary classification models, and it is influenced by the choice of the classification threshold. Understanding this trade-off is crucial for optimizing a model's performance based on the specific goals and requirements of a given application.

Additionally, the study was able to evaluate the performance of the proposed method against the existing method using standard decision support evaluation metrics. However, the computational time of the proposed enhancement was not measured against the existing method. This is a key index to evaluating the quality of the models.

Recommendation

Understanding this trade-off is crucial for optimizing a model's performance based on the specific goals and requirements of a given application. We recommend that future researches explore this opportunities and further evaluate the computational time of the proposed enhancement against the existing method as an index to evaluating the quality of the models.

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