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Skin Cancer Screening Using Deep Learning And Convolution Neural Network

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APPROVAL FORM

The undersigned certify that they have supervised the student Accuman A Mafuva's dissertation entitled skin cancer screening using machine learning and convolution neural network submitted in Partial fulfilment of the requirements for the Bachelor of Computer Science Honours Degree of Bindura University of Science Education.

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ABSTRACT

Skin lesion is a severe disease in world-wide extent. Early detection of melanoma in dermoscopy images significantly increases the survival rate. However, the accurate recognition of melanoma is extremely challenging due to premature assumption and human error emerging from fatigue and inconsistent frame mind. Hence, reliable automatic detection and classification detection skin tumours is very useful to increase the accuracy and efficiency of pathologists. On the other hand, Artificial intelligence is becoming the major thing of this high-tech industries. The innovation directed by the best tech companies are affecting industry verticals such as auto, finance, retail, manufacturing and to be precise, healthcare. This has called for medical industry to adopt Artificial Intelligence in automating medical operations. In this paper, the researcher proposed a deep learning system to address lesion dermoscopic feature extraction and lesion classification. The system entailing of convolutional neural networks is proposed to produce the classify skin lesions. Although there are some screening systems already, they are still restrictive and use specialised and expensive tools. The proposed system enables the users (pathologists) to take a picture of the lesion from a dermatoscope, make image classification print the class of the lesion and probability of likeliness.

DEDICATION

This report is dedicated mostly to my lovely parents and siblings for the great love l have received from them socially, financially, theologically, physically and academically as well.

ACKNOWLEDGEMENT

Foremost, I would like to appreciate the Almighty God for the charitable time, strength and aptitude that pushed me through my final year dissertation. Secondly, my gratitude goes to Bindura University of science education academic staff that has imparted their vast knowledge that has assisted me during my time at Bindura University of Science Education. Special thanks go to my supervisor, Dr Gombiro for his unwavering guidance as I worked through my research project. Worth mentioning is the invaluable support and guidance that I constantly got throughout the course of my research project from my co supervisors, Mr Muzurura and Mr Mapenduka for guiding and supporting me in several aspects of my research. Finally, I would like to thank my loving parent and siblings for their support, prayers, caring and sacrifices for educating and preparing me for my better tomorrow.

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Chapter 1

1. Problem Identification

1.1 Introduction

Skin cancer is among the most common types of cancer in the world. Melanoma is the most dangerous type of skin cancer, caused by over production of melanin pigments that change the colour and texture of skin, resulting as a dark lesion on the skin. Data indicate that the incidence of melanoma, which is a type of cancer that metastasizes rapidly, has increased alarmingly. However, screening inspection by visual analysis is limited by human visual ability, as well as human premature assumption, perception and sensitivity which in most cases the judgement can be affected by fatigue and frame mind. The tumour is an exceptional expansion of human cells that reproduce in an unrestricted way and that can be identified by a variation of colour and texture of the human tissue under study, making information contained in the images extremely valuable. As such this type of screening technique of visual inspection has infinite limitations in regard to precision and as such, innovative minds have risen to the challenge through the application of deep learning and other technologies to create more accurate detection and classification systems.

1.2. Background

(World Health Organisation, 2020) states that 1.2 million cases of skin cancer were recorded globally and that the figure will keep rising through the years. In Southern Africa, an estimated 130 000 cases have been recorded. Climate change is associated with shifts in global weather patterns, especially an increase in ambient temperature, and is deemed a formidable threat to human health. Skin cancer, a non-communicable disease, has been underexplored concerning a changing climate, (Caradee Y. Wright, 2019). Popular culture and fashion have influenced youth to apply lightening creams to be considered “beautiful/handsome”. Most of these creams cause multiple adverse reactions resulting in skin cancers. Although many may not view their actions as medically dangerous, numerous medical studies have already indicated that excessive usage of these skin whitening products can have an adverse effect that may cause skin cancer. According to (The Skin Cancer Foundation, 2021), the two main causes of skin cancer are the sun’s harmful ultraviolet (UV) rays and the use of UV tanning beds. With all these cases being recorded, there is a need for more accurate technological solutions to enable early detection and save our people.

1.3. Problem Statement

Most skin cancer cases go undetected until they are sufficiently mature to produce visible lumps. This is due to premature assumptions and poor judgement by human which is mostly affected by frame of mind and fatigue. Presently in most health institution, diagnosis of skin cancer is conducted by a medical practitioner who examines the patient's skin to determine whether there are skin changes over a certain period and if the lesions are likely to be skin cancer. Further testing is needed to confirm that diagnosis. A sample of suspicious skin is removed for testing (skin biopsy) that will determine whether you have skin cancer and, if so, what type of skin cancer you have, this sometimes can lead to wounds that will not heal. On the other hand, cases of misdiagnosis are on the rise, this is mainly due to incorrect assumptions and errors by the practitioner. In many cases, skin cancer is incorrectly diagnosed as eczema or another less serious disease. Misdiagnoses, failure to diagnose, and a delayed diagnosis can all be very dangerous for the patient, as cancer continues to progress without treatment (Paul & Perkins, 2021).

1.4. Aim of The Research

The aim of the research is to develop a skin cancer screening system that uses CNN.

1.5. Research Objectives

1. To design and implement a cancer screening system that uses CNN.
2. Evaluate the use of Convolution Neural Networks in skin cancer screening
3. To analyse the efficiency of convolution neural network in skin cancer screening

1.6 Research Questions

1. How is CNN based system going to screen skin cancer?
2. How can we evaluate the use CNN in skin cancer screening?
3. How is the system going to analyse the data?
4. How accurate and effective is CNN in skin cancer detection?

1.7 Research Propositions/Hypothesis

1. H0: Convolution Neural Networks will be able to classify skin cancer.
2. H1: Machine Learning and Convolution Neural Network will fail to classify skin cancer.

1.8 Justification of Research

Many people have lost their lives due to premature assumption and misinterpretation flaws in skin cancer diagnosis by medical practitioner. The implementation of a deep learning system that has the capabilities to screen skin cancer and, classifying lesions can greatly reduce the number of people who die due to skin cancer. There are many ways of classifying skin cancer, but each has its drawbacks, however, the use of machine learning may greatly reduce costs of human error due to premature assumption, fatigue and different frame mind. This research seeks to establish the efficiency of using deep learning to classify of skin cancer lesions behalf of the pathologists. It seeks to find ways of improving skin cancer classification by the use of deep learning and convolution neural network.

1.9 Assumptions

1. Assuming that every skin lesion is cancerous

1.10 Limitations

1. Accuracy and availability of dataset.
2. Processing power in training.

Chapter 2

2 Literature Review

Skin cancer classification has been in existence since 1985. Initially, the screening was conducted using a naked eye. With the advent of technology, full-body and digital photography, which augments visual inspection, are being adopted across different practice settings and specialty groups. In addition, many dermatologists used dermoscopy (also known as dermatoscopy, epiluminescence microscopy, or surface microscopy) to better examine the lesion. The dermoscopy is a magnifying lens equipped with a polarized or nonpolarized light source (to deflect surface reflection) that is held near the suspicious lesion. In addition, several imaging modalities emerged to help improve the diagnostic accuracy of visual inspection of pigmented skin lesions. These include epidermal genetic tape stripping, 'scent'/ 'odor' ultraviolet photography, fluorescence, ultrasound, laser Doppler, bio-electrical impedance, polarized light photography, 3-D histograms of colour mapping, multispectral imaging, and fully automated computer-based analysis, and thermography (National Center for Biotechnology Information, U.S. National Library of Medicine, 2011).

2.1 Skin Cancer

Skin cancer is the out-of-control growth of abnormal cells in the epidermis, the outermost skin layer, caused by unrepaired DNA damage that triggers mutations. These mutations lead the skin cells to multiply rapidly and form malignant tumours. The main types of skin cancer are basal cell carcinoma (BCC), squamous cell carcinoma (SCC), melanoma, and Merkel cell carcinoma (MCC). (The Skin Cancer Foundation, 2021).

2.2 Causes of skins cancers

According to (The Skin Cancer Foundation, 2021), the two main causes of skin cancer are the sun's harmful ultraviolet (UV) rays and the use of UV tanning beds. The good news is that if skin cancer is caught early, dermatologist can treat it with little or no scarring and high odds of eliminating it. Often, the doctor may even detect the growth at a precancerous stage, before it has become a full-blown skin cancer or penetrated below the surface of the skin.

2.3 Types of skin cancer

There are three major types of skin cancers namely: basal cell carcinoma (BCC), squamous cell carcinoma (SCC) and melanoma. The first two skin cancers are grouped together as non-melanoma cancers.

2.3.1 Basal cell carcinoma

(The Skin Cancer Foundation, 2021) defines Basal cell carcinoma as the cancer that occurs due to DNA damage from exposure to Ultraviolet (UV) radiation from the sun or indoor tanning triggers changes in basal cells in the outermost layer of the skin (epidermis), resulting in uncontrolled growth.

2.3.2 Squamous cell carcinoma

Most squamous cell carcinoma of the skin result from prolonged exposure to ultraviolet (UV) radiation, either from sunlight or from tanning beds or lamps. It is usually not life threating though it can be aggressive and spread other parts of the body (Mayo Clinic, 2021).

2.3.3 Melanoma

As stated by (American Cancer Society, 2021), melanoma is a type of cancer that develops when melanocytes (the cells that give the skin its tan or brown colour) starts to grow out of control. It is the most dangerous because it is more likely to spread to other parts of the body if not caught or treated early.

2.4 Skin Cancer Screening Techniques.

2.4.1 Naked Eye

Skin cancer is the most common malignancy in the world. Health care providers and patients alike are tasked with identifying suspicious skin lesions to diagnose skin cancers early and treat them quickly. The normal pathway to a skin cancer diagnosis is visual, with a dermoscopic assessment of the lesion followed by biopsy and histopathologic evaluation. (Dorrell DN, 2019)

2.4.2 Biopsy

In many cases, a doctor will remove the whole growth. During this procedure, he will numb the area before removing a tissue sample. There are several different biopsy methods, such as an excisional biopsy in which the doctor removes the entire growth is often sufficient to treat the skin cancer. Other types of biopsies include a shave biopsy, in which the doctor shaves off the top layers of the lesion, and a punch biopsy, in which the practitioner uses a special tool to cut a tiny round piece of the tumour, including deeper layers of the skin. He may also take a biopsy of any suspicious lymph nodes to see if they contain cancer cells.

2.4.3 Computer-Aided Diagnosis Support Systems.

(Vannier, 2013) states that, the usual clinical practice of melanoma diagnosis is a visual inspection by the dermatologist, and it is a bit disappointing. However, dermoscopy is a non-invasive diagnostic technique that links clinical dermatology and dermatopathology by enabling the visualization of morphological features which are not discernible by examination with the naked eye. There are different techniques, like solar scan, epiluminescence microscopy (ELM), cross-polarization epiluminescence (XLM), and side transillumination (TLM), that can greatly increase the morphological details that are visualized. Thus, they provide additional diagnostic criteria to the dermatologist. Dermoscopy enables better diagnosis as compared to unaided eye with an improvement in diagnostic sensitivity of 10–30%. However, it has also been demonstrated that dermoscopy may lower the diagnostic accuracy in the hands of inexperienced dermatologists since this method requires a great deal of experience to differentiate skin lesions. As described in only experts have arrived at 90% sensitivity and 59% specificity in skin lesion diagnosis, while for less trained doctors these figures show a significant drop to around 62%-63% for general practitioners.

2.5 Machine Learning

Emerj Artificial Intelligence Research (2021) defines Machine Learning as the science of getting computers to learn and act like humans do, and improve their learning over time in autonomous fashion, by feeding them data and information in the form of observations and real-world interactions. Furthermore, Machine learning algorithms create a computational template centred on test data, so that projections or choices can be made without explicit programming for the assignment (Koza, Forest & David, 1996). It is subset of artificial intelligence based on the concept that, with minimal human interference, systems can learn from information, identify trends, and make choices. Through machine learning a software program can understand its surroundings and make choices appropriately based on what they obtain.

2.6 Types of machine learning

The three most common kinds of machines that are monitored, unattended and strengthening learning formally known as supervised, unsupervised and reinforcement learning.

2.6.1 Supervised Machine Learning

This algorithm consists of a target / outcome variable (or dependent variable) which is to be predicted from a given set of predictors (independent variables). Using these set of variables, a function is generated that map inputs to desired outputs. The training process continues until the model achieves a desired level of accuracy on the training data. Examples of Supervised Learning: Regression, Decision Tree, Random Forest, KNN, Logistic Regression etc. (Abdi, 2016).

2.6.2 Unsupervised Learning

Is a term that refers to Hebbian teaching, allied with teacher-free learning, also known as self-organization, is a method of modelling input probability density (Hinton & Sejnowski 1999). A central framework of unmonitored learning is statistical density estimation, although unsupervised teaching involves many other fields involving the summary and explanation of data characteristics.

2.6.3 Reinforcement Learning

Is a machine learning zone involved with how software officials should act in an area to maximize some cumulative compensation concept? It varies from supervised teaching in that marked input / output duos do not need to be present and sub-optimal activities do not need to be clearly fixed. The focus is instead on discovering equilibrium between exploring and exploiting present understanding (Kaelbling, Littman, & Moore, 2011).

2.7 Neural Networks

Neural networks are computing systems with interconnected nodes that work much like neurons in the human brain. Using algorithms, they can recognize hidden patterns and correlations in raw data, cluster and classify it, and – over time – continuously learn and improve (SAS Institute Inc., 2021). Neural networks are also ideally suited to help people solve complex problems in real-life situations. They can learn and model the relationships between inputs and outputs that are nonlinear and complex; generalize and inferences; reveal hidden relationships, patterns and predictions; and model highly volatile data (such as financial time series data) and variances needed to predict rare events (such as cancer detection).

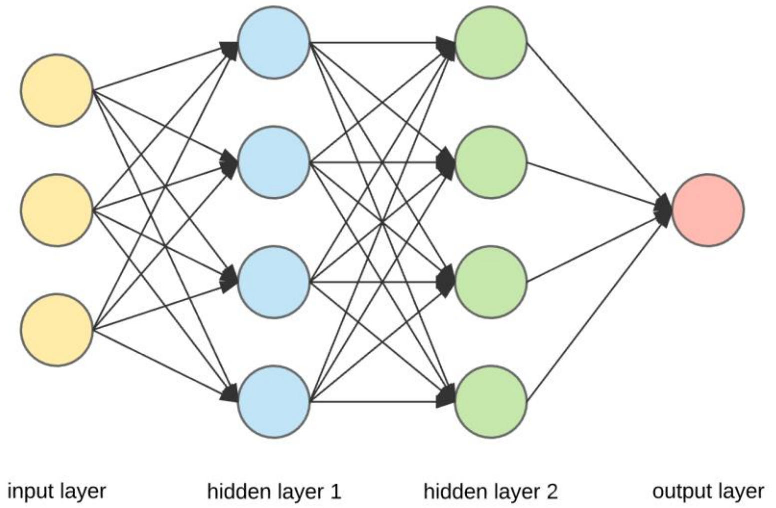


Figure 1 Neural Network

2.8 Convolutional Neural Network

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets could learn these filters/characteristics.

2.9 Backpropagation Algorithm

Great Learning, (2020) defines the backpropagation algorithm as an algorithm that trains some given feed-forward Neural Network for a given input pattern where the classifications are known to us. At the point when every passage of the example set is exhibited to the network, the network looks at its yield reaction to the example input pattern. After that, the comparison done between output response and expected output with the error value is measured. Later, we adjust the connection weight based upon the error value measured.

2.10 Review of previous research.

In this section, the author reviews some research works which related to this study due to their use of convergent techniques for texture analysis. Li (2018) proposed two deep learning methods to address three main tasks emerging in the area of skin lesion image processing, that is, lesion segmentation, lesion dermoscopic feature extraction and lesion classification. The proposed deep learning frameworks were evaluated on the ISIC 2017 dataset. Experimental results showed the promising accuracies of these frameworks, that is, 75.30% for task 1, 84.80% for task 2 and 91.20% for task 3 were achieved.

Hekler et al (2019). execute deep learning methods to classify histopathologic diagnosis of melanoma, to augment the human evaluation, and contrasted the outcome with skilful histopathologists.

Yunfei et al. (2015) proposed a deep residual model for classification of skin pigmented lesions, which upgraded by class weight update dynamically, Excitation, and Squeeze module in batches.

Harangi et al (2018), utilize an ensemble DCNN (deep convolutional neural network) method, where they combine the result of four different architectures with improving the accuracy of the ISBI 2017 dataset. Rather than training CNN (Convolutional Neural Network) from scratch, Kawahara et al. (2016) attempted to employ pre-trained ConvNet as their feature extractor, and they classify ten classes of non-dermoscopic skin images.

Recently, Vamvakas (2020) proposed the solution of a challenge in the diagnosis of magnetic resonance images, using advanced techniques such as Diffusion Tensor Imaging—distinguishing ambiguous images in the appearance of Glioblastoma Multiforme and solitary metastasis, using 3D textural resources with GLCM.

Furthermore, Jennitta (2020), using GLCM and Local Standard Descriptor parameters, applied to magnetic resonance images of the brain, showed a promising approach to medical diagnosis.

Hiba Asri (2017), with the objective of diagnosing breast cancer, used machine learning techniques, such as—Support Vector Machine (SVM), Decision Tree, Naive Bayes and K closest neighbours, in the Wisconsin Breast Cancer database. The results proved that the SVM had the best accuracy—97.13%.

Meenakshi M M, (2019) designed a model is under three phases comprising of data collection and augmentation, designing model and finally prediction. They used multiple AI algorithms like Convolutional Neural Network and Support Vector Machine and amalgamated it with image processing tools to form a better structure, leading to higher accuracy of 85%.

2.11 Proposed System

Artificial intelligence is becoming the major thing of this high-tech industries. The innovation directed by the best tech companies are affecting industry verticals such as auto, finance, retail, manufacturing and to be precise, healthcare. This has called for medical industry to adopt Artificial Intelligence in automating medical operations. Presently visual inspection techniques are used in screening skin cancer; however, it is characterised by misinterpretation flaws led by premature assumption, fatigue or different frame of mind of medical professionals. Following this train of thought it becomes evident that the utilisation of Machine Learning and CNN in skin cancer classification may reduce the technical requirements of operation and ultimately costs on the user without diminishing the accuracy of the diagnosis.

Chapter 3

3.1 Introduction

The previous chapter was on literature review, an overview of what is known and of what is not known about the subject matter. It is a process of understanding a field of study by analysing published, unpublished scholarly and research work. The aim of this chapter is to define the strategies and tools used to achieve the proposed objectives of research and system. With the help of the information attained in the previous chapter the author formulated the necessary methods to build a solution and be able to make choices among competing strategies to achieve the expected results of the research.

3.2 Research Design

It is the researcher's overall for answering the research questions (Polit and Beck,2012). The process starts with determining a research design that intends to specify how the researcher intends to attain the goals of the study. The research design guides the author through the various stages of the research project. The section focuses mainly on decisions about methods of data collection, that is the data to be collected, the type of data to be collected, the method or techniques of data analysis, and the sources of data. The core objective of this stage is to ensure that an operative, proficient, sustainable and reliable system is designed.

The author decided to use the experimental research design as it allows him to observe changes and response of systems and objects as he changes or adjust factors. The author divided the dataset into train data and test data, which he then used for evaluation of improvement. The author created a skin cancer screening system.

3.3 Requirement Analysis.

It is essential to document all the functional and non-functional specifications of the required system. It is advisable to structure all incoming data, asses it, consider all the limitations which may arise on the customer's side, and come up with a ready-to-follow specification that meets the customer's needs. The research also considered types of limitations, such as availability of datasets and processing power during machine training, that may impede the design method.

3.3.1 Functional Requirements

- The system ought to be able to upload and analyse images of lesions of interest.
- The system should be in a position to classify given images.

3.3.2 Non-Functional Requirements.

They are often referred to as quality requirements and used to judge the performance of a system rather than its intended behaviour. The proposed system must be able to meet the following:

- The system must be reliable and accurate.
- The system is supposed to be user friendly.
- The system should be scalable.
- The system should have a relatively small response and decision time

3.4 Hardware Requirements

- A core i3 processor

3.5 Software Requirements

- Windows 10 Operating system.
- PyCharm development tool.

3.6 System Development.

This describes the overview of the system and how it was developed to produce the results. It specifies all the software tools and models used in the development of the system.

3.7 Development Methodology

Software prototyping refers to the process of visualizing a software product before it has been created. Creating software from scratch requires a great investment in the form of time, money, and effort. That is why most clients prefer to have a visual prototype developed before work is put into the development of the actual product. The prototype acts as a ‘model’ closely replicating the functionality, of the product that the client has in mind. All the requirements of the project have been identified and all the tools are in place hence the waterfall model is the best candidate for such a project.

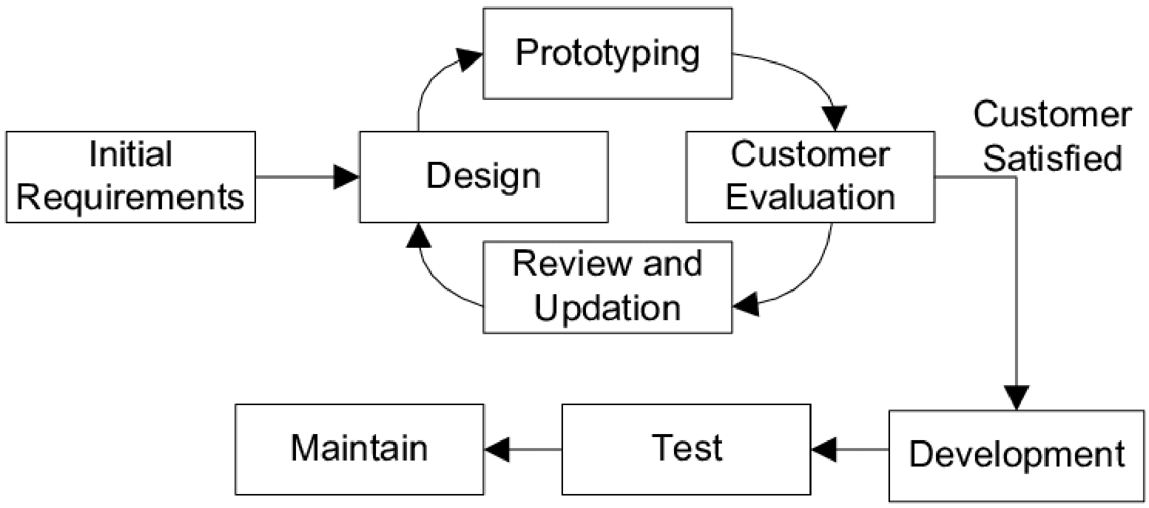


Figure 2 Development Methodology

3.8 Prototyping

Prototyping is the process of building a model of a system. In terms of an information system, prototypes are employed to help system designers build an information system that intuitive and easy to manipulate for end users. It is an iterative process that is part of the analysis phase of the systems development life cycle.

During the requirements determination portion of the systems analysis phase, system analysts gather information about the organization's current procedures and business processes related the proposed information system. In addition, they study the current information system, if there is one, and conduct user interviews and collect documentation. This helps the analysts develop an initial set of system requirements.

Prototyping can augment this process because it converts these basic, yet sometimes intangible, specifications into a tangible but limited working model of the desired information system. The user feedback gained from developing a physical system that the users can touch and see facilitates an evaluative response that the analyst can employ to modify existing requirements as well as developing new ones.

3.8.1 Benefits of prototyping

- Reduces development time.
- Reduces development costs.
- Requires user involvement.
- Developers receive quantifiable user feedback.
- Facilitates system implementation since users know what to expect.

- Results in higher user satisfaction.
- Exposes developers to potential future system enhancements.

3.8.2 Disadvantages of prototyping

- Can lead to insufficient analysis.
- Users expect the performance of the ultimate system to be the same as the prototype.
- Developers can become too attached to their prototypes
- Can cause systems to be left unfinished and/or implemented before they are ready.
- Sometimes leads to incomplete documentation.
- If sophisticated software prototypes (4th GL or CASE Tools) are employed, the time saving benefit of prototyping can be lost.

Apart from the methodology the system was also developed using the following tools:

3.9 Python

According to (Python Software Foundation, 2021), Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together. Python's simple, easy to learn syntax emphasizes readability and therefore reduces the cost of program maintenance. Python supports modules and packages, which encourages program modularity and code reuse. The Python interpreter and the extensive standard library are available in source or binary form without charge for all major platforms and can be freely distributed.

3.10 TensorFlow

TensorFlow is an interface for expressing machine learning algorithms, and an implementation for executing such algorithms (Mart´ın Abadi, 2015).

3.11 Keras

It is a powerful and easy-to-use free open-source Python library for developing and evaluating deep learning models. It wraps the efficient numerical computation libraries Theano and TensorFlow and allows you to define and train neural network models in just a few lines of code.

3.12 Summary of how the system works

The system is responsible for making decisions basing on the inputs extracted from images of interest and what the system was trained. Ideally, the user uploads images of interest, system performs features extraction to define inputs. These extracted features or inputs are then run through the model (system) which then predicts the class. On input acceptance, system uses probabilities and basing on the Neural Network principles to decide on whether the lesion is malignant or benign.

3.13 System Design

The requirements specification document is analysed, and this stage defines how the system components and data for the system satisfy specified requirements.

3.14 Convolutional Neural Network

The author used a CNN algorithm to create a model for classification of skin cancer. Below is a snippet of the convolutional neural network used in the system.

```
model = Sequential()

model.add(Conv2D(16, kernel_size=(3, 3), input_shape=(28, 28, 3), activation='relu', padding='same'))

model.add(Conv2D(32, kernel_size=(3, 3), activation='relu'))

model.add(MaxPool2D(pool_size=(2, 2)))

model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', padding='same'))

model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))

model.add(MaxPool2D(pool_size=(2, 2), padding='same'))

model.add(Flatten())

model.add(Dense(64, activation='relu'))

model.add(Dense(32, activation='relu'))

model.add(Dense(7, activation='softmax'))
```

The model accepts an image and convert it to a array of pixel values that maps to 28 by 28 matrix. The matrix is further flattened into a single column matrix that is fed into the input column of the dense layer of the matrix. This model has two hidden layers and the output layer with 7 neurons for classification of the lesion using softmax activation function.

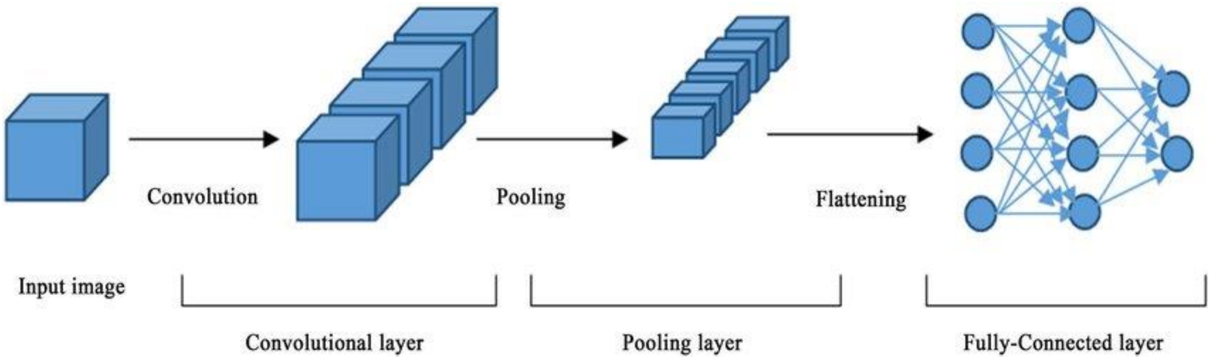


Figure 3Convolutional Neural Network

3.15 Dataflow Diagrams

A DFD is defined as a diagraph together with a binary relation, called the precedence relation. The nodes of the digraph represent the processes, data stores, and external entities, and the directed edges represent the data flows. The precedence relation for a DFD is an abstraction of the functional semantics and specifies the "is-used-to-produce" relationships among the data flows.

It is an important visual method for modelling a system's high-level detail by describing how input data is converted to output results through a continuance of functional transformations. The flow of data in a DFD is named to indicate the nature of data used. DFDs are a type of information development, and as such provides an important insight into how information is transformed as it passes through a system and how the output is displayed.

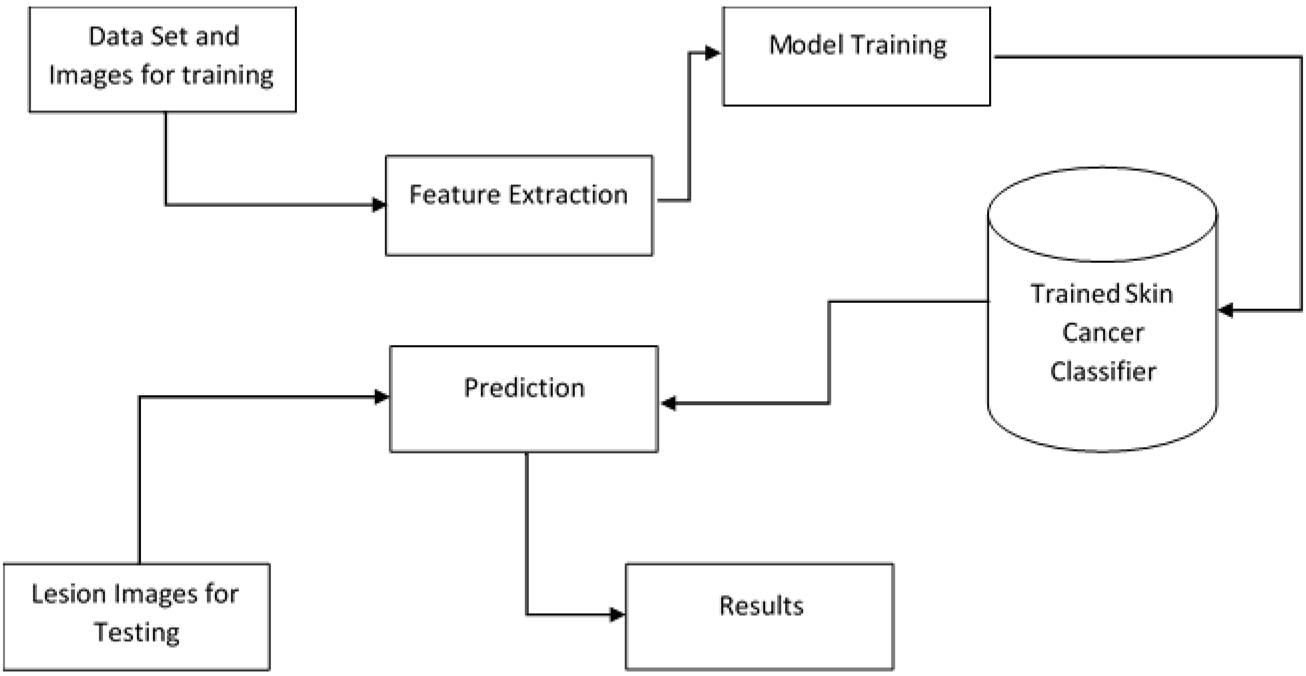


Figure 4 Data Flow Diagram

3.15 Proposed System flow chart

Flowcharts are an efficient way of bridging the communication divide between programmers and end users. They are flowcharts specialized in distilling a significant amount of data into comparatively few symbols and connectors.

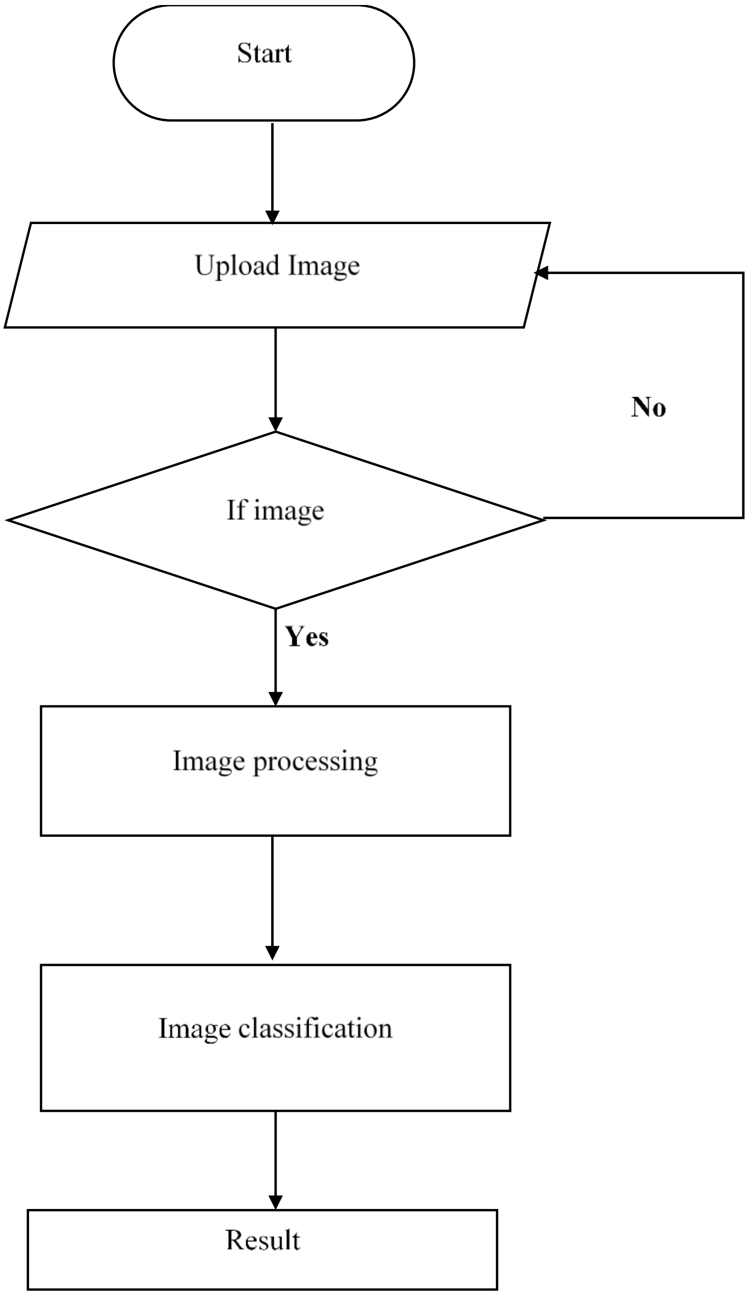


Figure 5 Proposed System Flow Chart

3.16 Training Model

The model was trained using the Neural Network algorithm for deep learning after the researcher made consideration of other classification algorithms as shown in the literature review. The analysis of the algorithm to be used in the training of the model was done using python programming language. The neural network layers are added with respect to input provided by the dataset so that they get all the data available for training and below is a piece of code that was used in the development of the model.

```
# creating a model
model = Sequential()
model.add(Conv2D(16, kernel_size=(3, 3), input_shape=(28, 28, 3), activation='relu', padding='same'))
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2)))
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2), padding='same'))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dense(32, activation='relu'))
model.add(Dense(7, activation='softmax'))
model.summary()

# defining a callback function
callback = tf.keras.callbacks.ModelCheckpoint(filepath='best_model.h5', monitor='val_acc', mode='max', verbose=1)

# model training
model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
history = model.fit(X_train, Y_train, validation_split=0.2, batch_size=128, epochs=20, callbacks=[callback])
```

Figure 6 Model of the system (CNN)

3.18 File Structure

This section describes how data is going to be organized in the system. It outlines the files present in the system and the format of the data kept in the files. The author decided to use csv dataset, the dataset was divided in two, 80% of the data is for the training memory and 20% for the evaluation memory. Illustrated below is the dataset used.

	pixel0000	pixel0001	pixel0002	pixel0003	pixel0004	pixel0005	pixel0006	pixel0007	pixel0008	pixel0009	...	pixel2343	pixel2344	pixel2345	pixel2346	pix
0	192	153	193	195	155	192	197	154	185	202	...	173	124	138	183	
1	25	14	30	68	48	75	123	93	126	158	...	60	39	55	25	
2	192	138	153	200	145	163	201	142	160	206	...	167	129	143	159	
3	38	19	30	95	59	72	143	103	119	171	...	44	26	36	25	
4	158	113	139	194	144	174	215	162	191	225	...	209	166	185	172	
5	8	1	3	19	5	10	26	8	13	34	...	12	3	7	5	
6	194	147	137	197	148	139	197	148	132	200	...	211	160	163	211	
7	161	121	105	169	128	119	172	129	116	176	...	141	103	92	87	
8	125	84	85	165	114	118	181	120	125	188	...	119	80	79	62	
9	228	179	194	227	174	191	226	165	182	215	...	217	142	156	219	

10 rows × 2353 columns

Figure 7 CSV Dataset for training the system

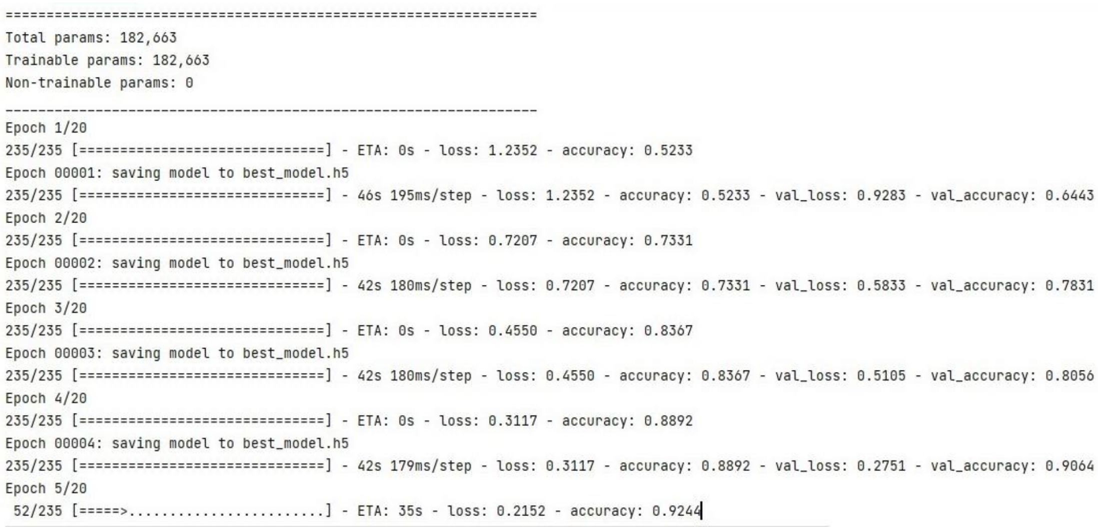
3.19 Implementation of the evaluation function

3.19.1 Data collection methods

The author used observation as a data collection tool. The author ran multiple tests whilst observing the system's responses. The observations gave the researcher a room to analyse the accuracy of the system.

3.19.2 Implementation

The proposed system was developed using Keras toolbox. The patch dataset was separated into the training set and the validation set according to the percentages of 80:20, respectively. The network was optimized by Adam optimizer with an initial learning rate of 0.01. The learning rate decreases with gamma = 0.1. The network was trained on a single CPU (Intel Core i5, 4GB RAM) and was observed to converge after 20 epochs of training



```
=================================================================
Total params: 182,663
Trainable params: 182,663
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
235/235 [==============================] - ETA: 0s - loss: 1.2352 - accuracy: 0.5233
Epoch 00001: saving model to best_model.h5
235/235 [==============================] - 46s 195ms/step - loss: 1.2352 - accuracy: 0.5233 - val_loss: 0.9283 - val_accuracy: 0.6443
Epoch 2/20
235/235 [==============================] - ETA: 0s - loss: 0.7207 - accuracy: 0.7331
Epoch 00002: saving model to best_model.h5
235/235 [==============================] - 42s 180ms/step - loss: 0.7207 - accuracy: 0.7331 - val_loss: 0.5833 - val_accuracy: 0.7831
Epoch 3/20
235/235 [==============================] - ETA: 0s - loss: 0.4550 - accuracy: 0.8367
Epoch 00003: saving model to best_model.h5
235/235 [==============================] - 42s 180ms/step - loss: 0.4550 - accuracy: 0.8367 - val_loss: 0.5105 - val_accuracy: 0.8056
Epoch 4/20
235/235 [==============================] - ETA: 0s - loss: 0.3117 - accuracy: 0.8892
Epoch 00004: saving model to best_model.h5
235/235 [==============================] - 42s 179ms/step - loss: 0.3117 - accuracy: 0.8892 - val_loss: 0.2751 - val_accuracy: 0.9064
Epoch 5/20
 52/235 [=====>........................] - ETA: 35s - loss: 0.2152 - accuracy: 0.9244
```

Figure 8 Screenshot of the system in training mode

3.19.3 Screenshot of the system in training mode

After the model training process, it had an accuracy 0.9733 and loss of 0.12

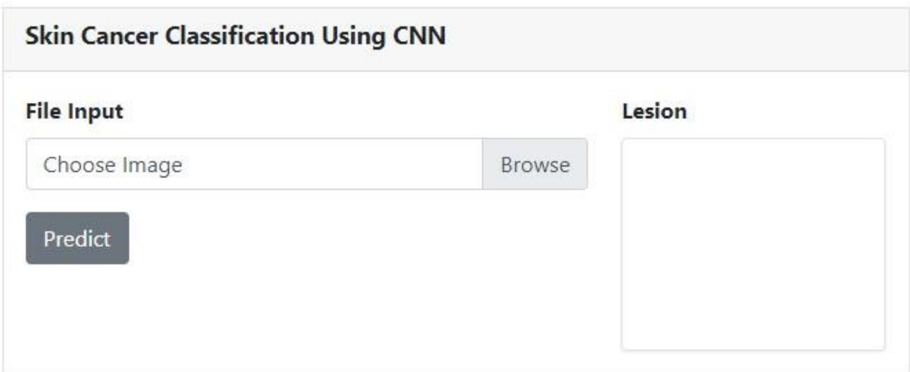


Figure 9 Screenshot of the system in after training

3.19.4 Screenshot of the system in classification mode

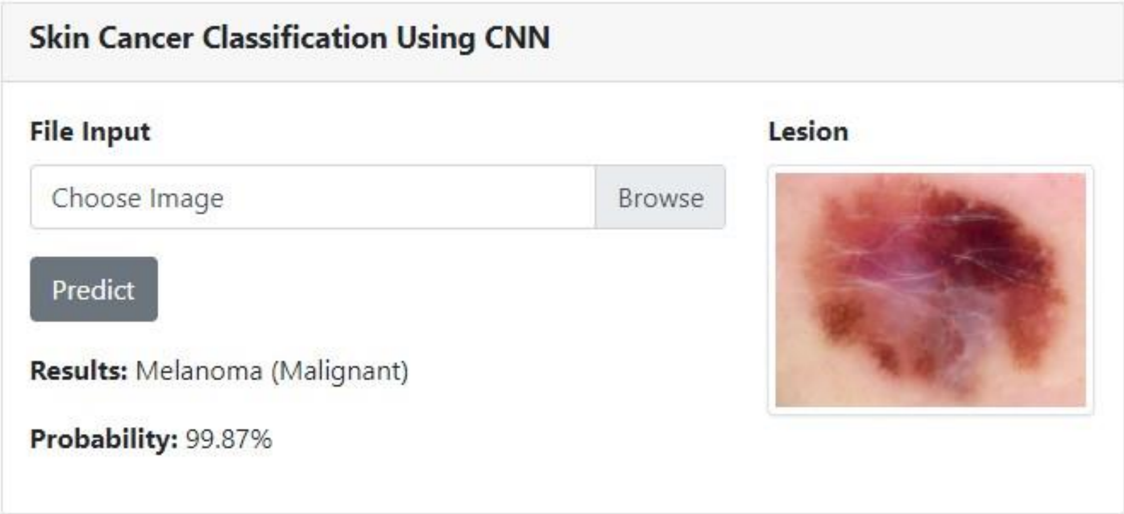


Figure 10 Screenshot of the system in classification mode

3.20 System Evaluation

3.20.1 Testing

Testing is a vital part of the development process and the tests were undertaken whilst the tabulating results. The testing is thus measured against the functional and non-functional requirements as outline in the previous chapter.

3.20.2 Black box Testing

Black box testing enables a user without the knowledge of the internal structure of the system to test it against the functional and sometimes the non-functional requirements of the system. It mainly focused on classifying lesions of skin cancer over given images using deep learning and convolution neural network technology. Thus, the main purpose of black box testing was to test if the system worked as per expected in requirement document.

Moreover, white box testing was conducted, it involved testing of the internal structure is being known to tester who is going to test the software.

3.21 Summary

This chapter mainly focused on the methodology used in the development of the system and how it was designed. The system functionalities and how the system data flows from the start to the end are as well illustrated in this chapter. The results obtained from the developed solution where discussed and analysed in the following chapter. The next chapter also draws a conclusion on the obtained results.

Chapter 4

4.0 Data Presentation, Analysis and Interpretation

4.1 Introduction

The previous chapter was on research methodology and this chapter is now focusing on the System itself and Data Presentation. The researcher managed to develop the screening system that uses deep learning and Convolution Neural Network. Users upload images of the lesion on the system and using the trained model, prediction are made basing on how the network was trained. Accuracy and performance were used to determine the efficiency and effectiveness of the developed solution. Data collected was analysed to produce eloquent results. The developed system's performance was well observed using different images and the outcome was presented in a table format. The white box, black box and unit testing played major roles in determining the system behaviour.

4.2 System's self-evaluation

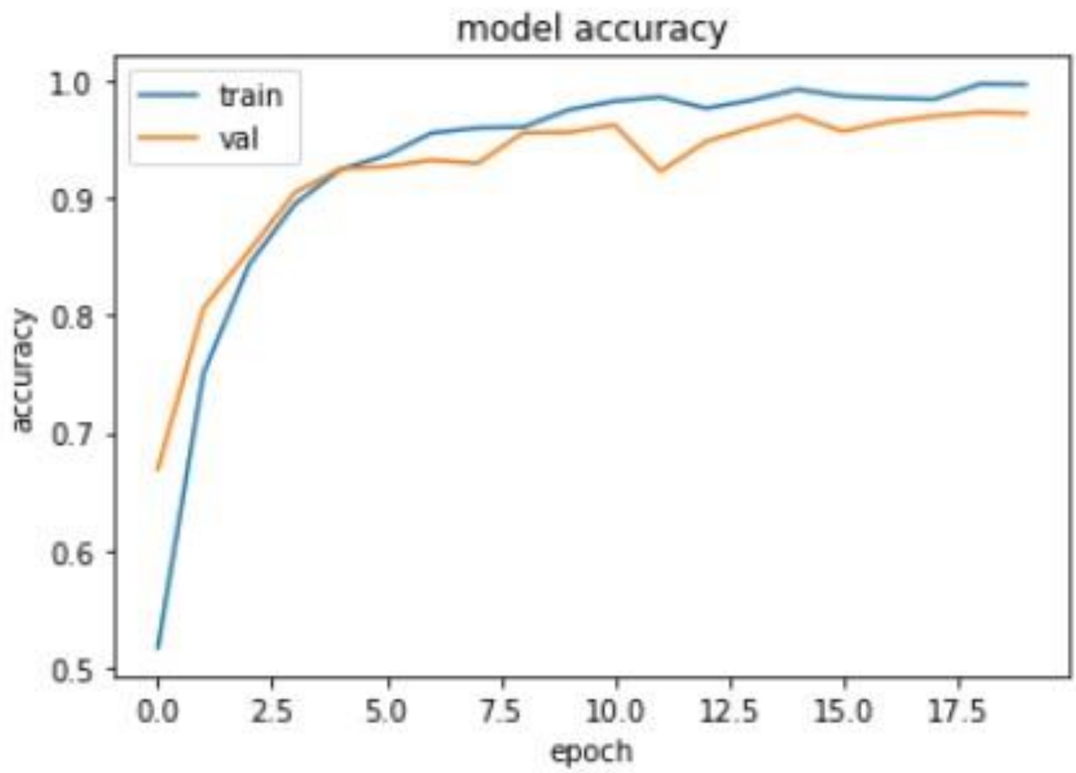


Figure 11 Model Accuracy during training phase

The graph above shows the model's accuracy improving with respect to number of epochs, which is the number in which data is passed from input to out and back fourth during the training phase. The accuracy was of model was 0.9733 after running 20 epochs and the loss as illustrated in the graph below it was 0.1214

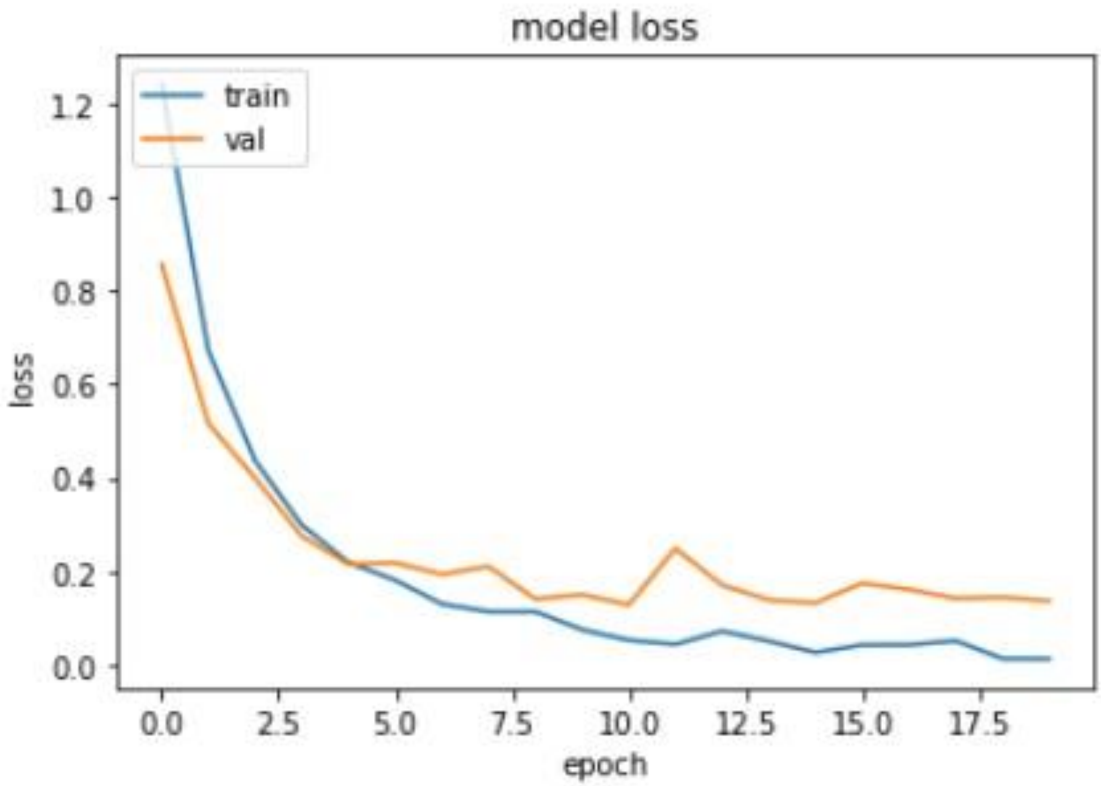


Figure 12 Model loss during training

The researcher managed to take screenshot of the system during test runs.

4.3 Screenshots of the system.

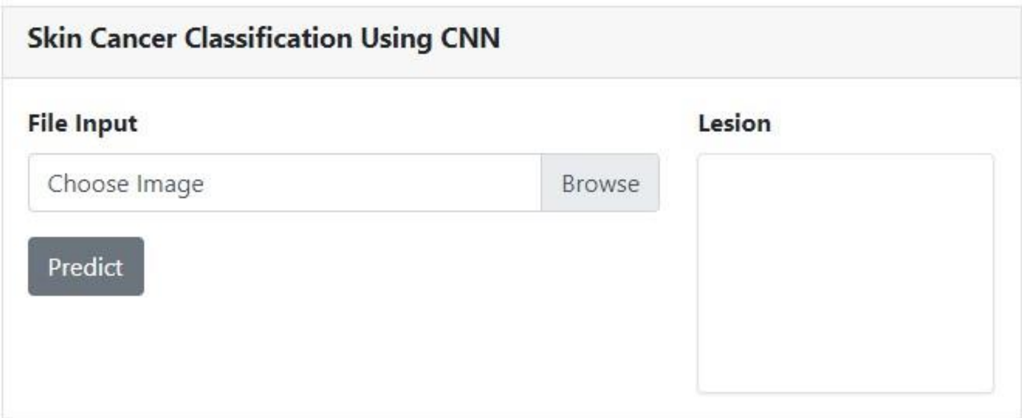


Figure 13 Screenshot of the system waiting for input

4.4 Test Run 1, Melanoma

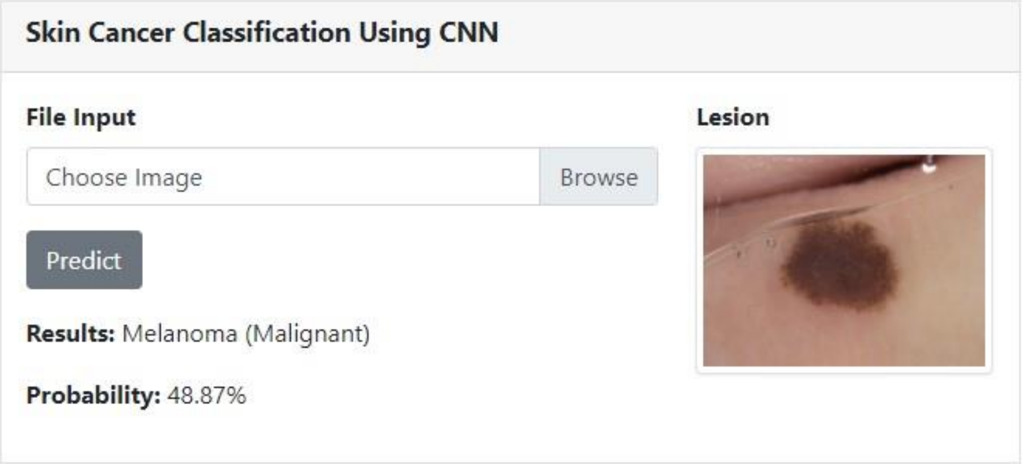


Figure 14 Melanocytic Nevi

Test run 2, Melanocytic Nevi

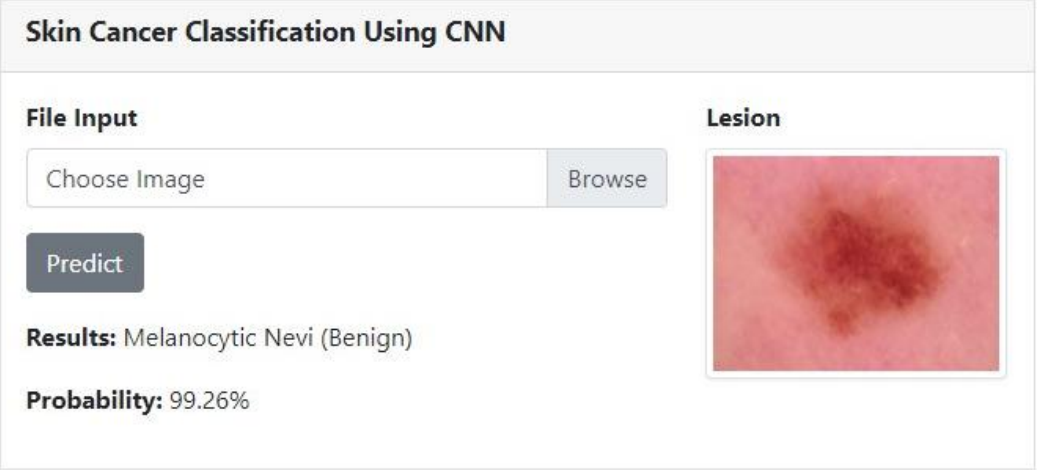


Figure 15 Melanocytic Nevi

Test run 3: Basal Cell Carcinoma

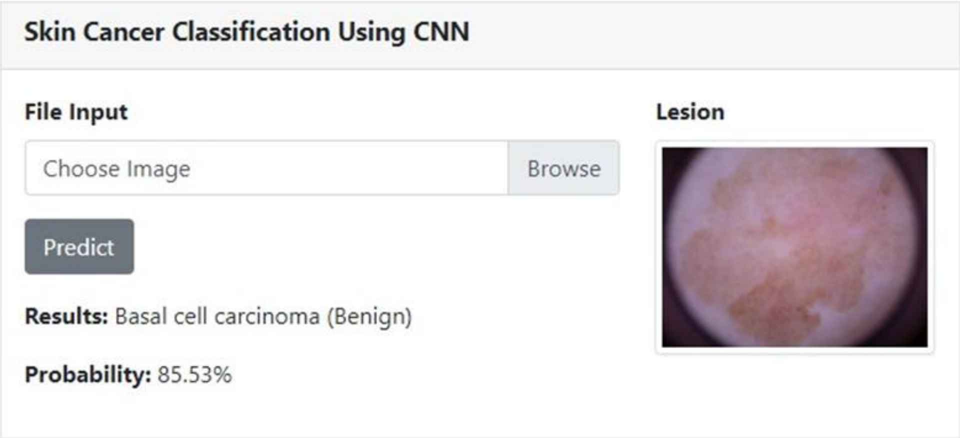


Figure 16 Basal Cell Carcinoma

Test run 4, Melanocytic Nevi

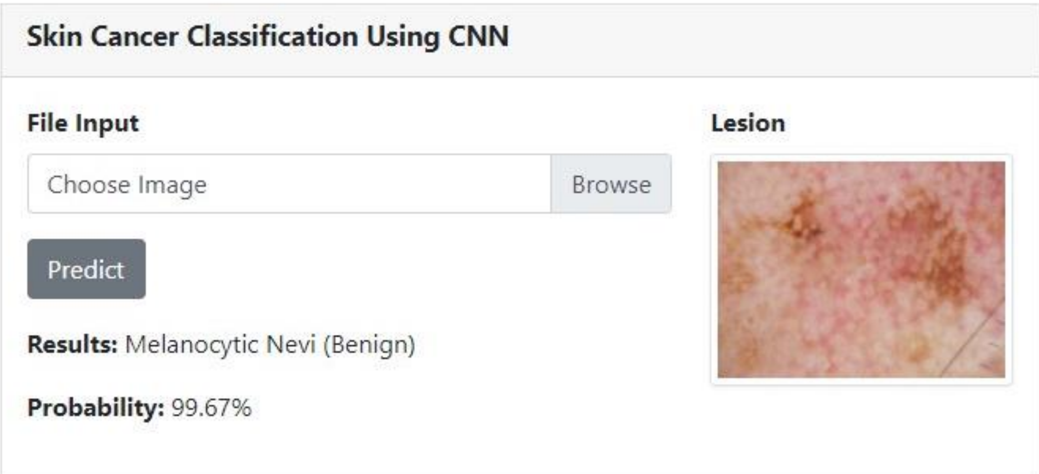


Figure 17 Melanocytic Nevi

Test run, Melanocytic Nevi

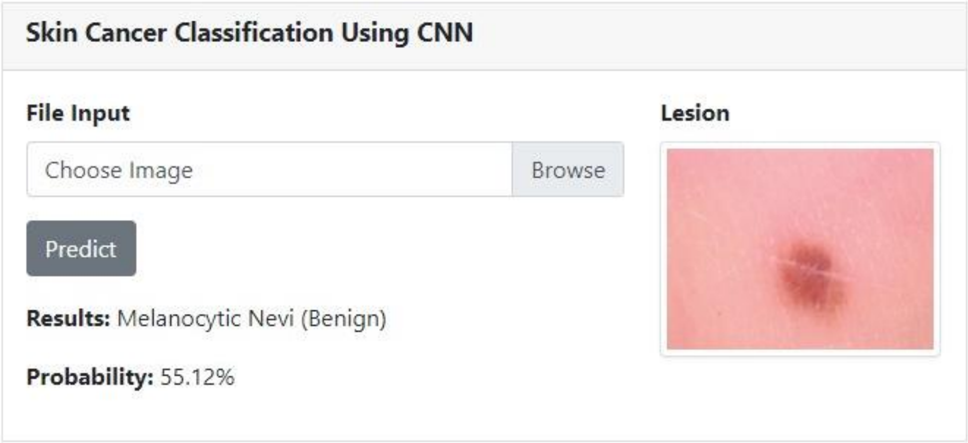


Figure 18 Melanocytic Nevi

Test run 6, Basal Cell Carcinoma

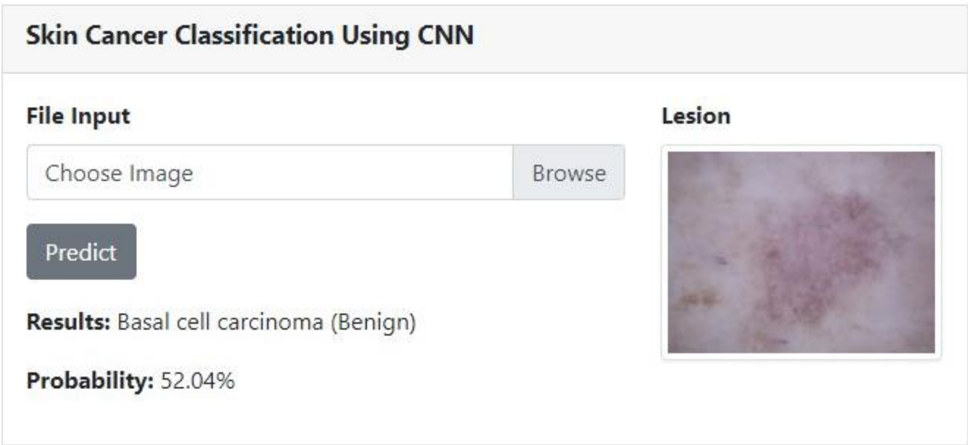


Figure 19 Basal Cell Carcinoma

Test run 7, Melanoma

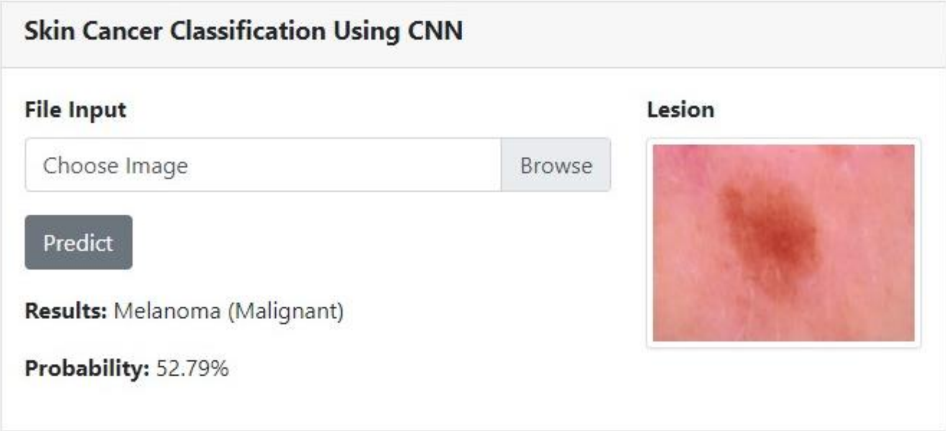


Figure 20 Melanoma

Test run 8, Melanoma

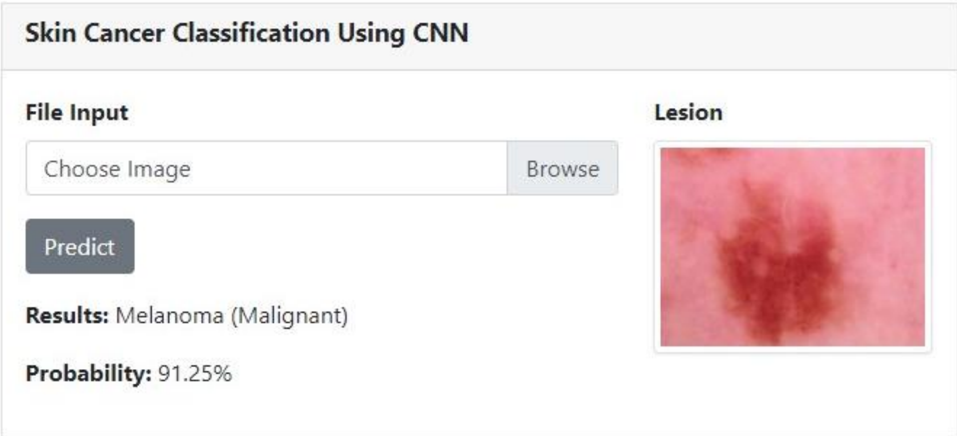


Figure 21 Melanoma

Test run 9, Melanocytic Nevi

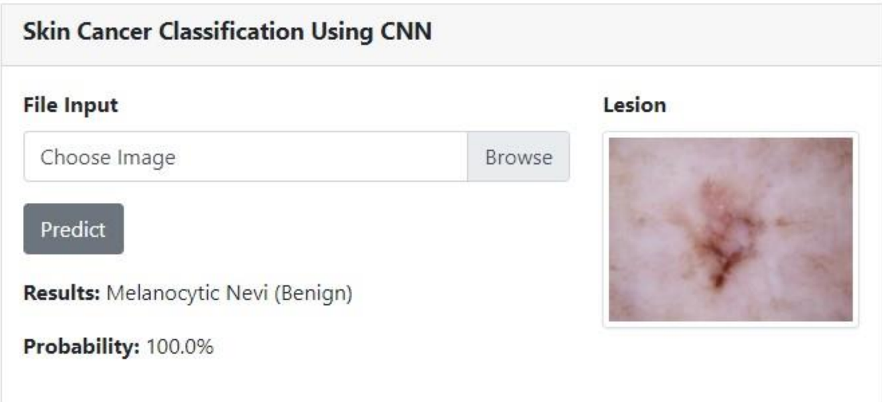


Figure 22 Melanocytic Nevi

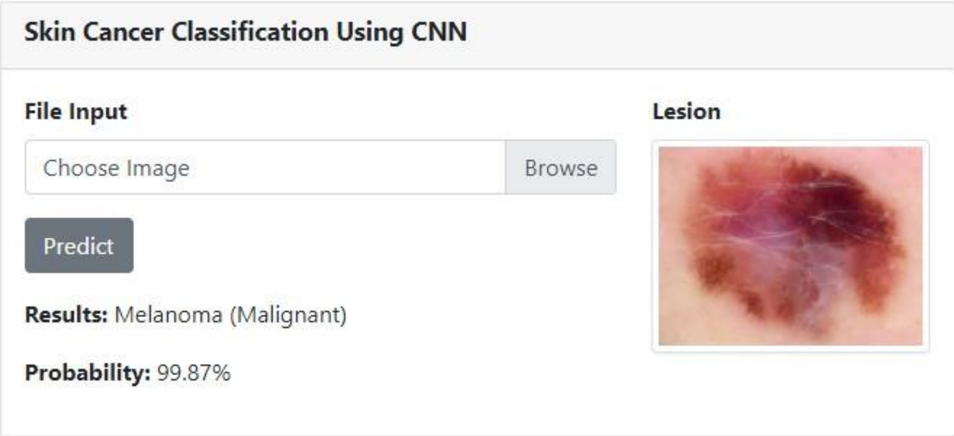
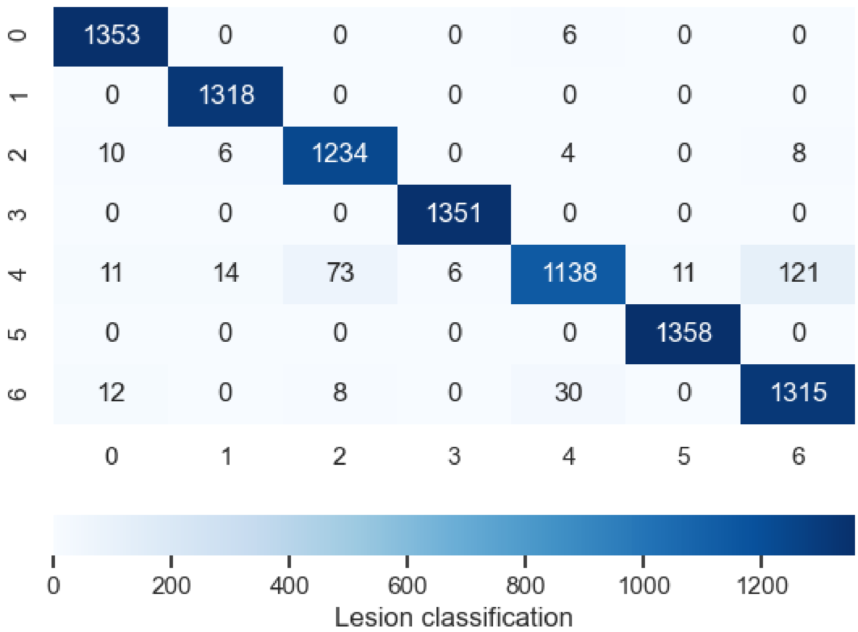


Figure 23 Melanoma

4.5 Evaluation Measure and Results

For the evaluation of results, metrics like Precision, Recall, F1 score, and Accuracy are calculated basing on the system observed system's output. The performance of the system is ranked according to its ability to classify images and the rate of falsehood after a training session. To test for the accuracy of the system a confusion matrix was used.

4.6 Confusion Matrix



Classification of skin cancer:

```
classes = {4: 'Melanocytic Nevi (Benign)',
           6: 'Melanoma (Malignant)',
           2: 'Keratosis-like lesions (Benign)',
           1: 'Basal cell carcinoma (Benign)',
           5: 'Pyogenic Granulomas (Benign)',
           0: 'Actinic keratoses (Malignant)',
           3: 'Dermatofibroma (Benign)'
           }
```

4.7 System accuracy, precision, recall and f1 score

Accuracy

- Ratio of correctly predicted observations to the total observations
    - Accuracy = (Tp + Tn) / (P + N)
    - Accuracy= **0.957814**

Precision

- Ratio of correctly predicted positive observations to the total predicted positive observations.
    - Precision= Tp / (Tp + Fp)
    - Precision= **0.959916**

Recall

- Ratio of correctly predicted to all observations in actual class.
    - Recall = Tp / (Tp + Fn)
    - Recall = **0.957814**

F1 Score

- It is the weighted average of Precision and Recall.
    - F1 Score = 2 Tp / (2 Tp + Fp + Fn)
    - F1 Score = **0.956317**

4.8 System Results

The following results were obtained after testing the system with different images from different sources. The results shows that there was no difference from the results obtained by system and those obtained by the practioner.

IMAGE ID	SYSTEM RESULT	PROBABILITY	EVALUATOR 1
ISIC_0029306	Melanoma (Malignant)	48.87	Melanoma (Malignant)
ISIC_0029307	Melanocytic Nevi (Benign)	99.26	Melanocytic Nevi (Benign)
ISIC_0029308	Basal cell carcinoma (Benign)	85.53	Basal cell carcinoma (Benign)
ISIC_0029309	Melanocytic Nevi (Benign)	99.67	Melanocytic Nevi (Benign)
ISIC_0029310	Basal cell carcinoma (Benign)	55.12	Melanocytic Nevi (Benign)
ISIC_0029311	Basal cell carcinoma (Benign)	52.04	Basal cell carcinoma (Benign)
ISIC_0029312	Melanoma (Malignant)	52.79	Melanoma (Malignant)
ISIC_0029313	Melanoma (Malignant)	74.29	Melanoma (Malignant)
ISIC_0029314	Melanoma (Malignant)	91.25	Melanoma (Malignant)
ISIC_0029315	Melanocytic Nevi (Benign)	100	Melanocytic Nevi (Benign)
ISIC_0029316	Melanoma (Malignant)	99.87	Melanoma (Malignant)

Conclusion

The test results indicated the solution had a high level of accuracy since it produced a 100% rate of accuracy as predicted by the evaluator in 10 test runs. The solution had a ninety-five (95%) percent accuracy from the confusion matrix. The high levels of accuracy of the system indicate a reduction of false predictions that emerge from premature assumption and misinterpretation flaws. During the testing phase the author realized that the solution can also be used to assist pathologist in classification of skin cancer, this was achieved by the continuous assessment of the system. Translating the rate of response, it implies that the provided solution can classify lesions in real time. This makes it easy to diagnose skin cancer in its early stages and save lives of people. Through deep learning one can teach the machine to detect lesions and classify the lesions accordingly. At this point the researcher saw it worthy to use Artificial Intelligence for learning/ automatic evaluation model generation and Convolutional Neural Network in decision making thus using deep learning and convolutional neural network is a viable method for reducing premature assumptions and errors in classifying the disease.

Chapter 5

5.0 Conclusion and Recommendations

5.1 Introduction

The author focused on presentation and analyses of collected results from the research on the previous chapter. This chapter focuses on recommendations, conclusions and future work as far as the skin cancer classification using deep learning and convolution neural network. Furthermore, this chapter looks at the lurches faced by the researcher during implementation of the research system under consideration.

5.2 Aims and Objectives Realization

The main aim of this research was to develop a system for skin cancer screening using deep learning and convolution neural network and be able to use this system in classifying skin cancer. The aim was fully achieved. The objectives set by the researcher were also accomplished. The first one, was to design and implement a cancer screening system that uses CNN, and this objective was achieved in chapter four when tests were done. Followed by evaluation of the use of Convolution Neural Networks in skin cancer screening then finally, analysis of efficiency of convolution neural network in skin cancer screening. The screening process will be more accurate and much faster, with less cost of acquiring skilled personnel in the medical field. The system's accuracy implied a reduction in premature assumption and misinterpretation flaws of human expects emerging from fatigue or different in frame mind.

5.3 Conclusion

Using deep learning and convolution neural networks greatly reduce misinterpretation flaws and premature assumptions by humans as it draws its decision in classification from large analysing large volumes of already known facts about nature of different types of skin cancer. With this small version of skin cancer screening, the system proved to be accurate and time saving in classification of skin cancer.

5.4 Recommendations

It is recommendable to use a powerful and more efficient computational machine to train and the system's model to reduce the training time taken especially when dealing with a large dataset which also possess a big variety of variations to be considered for the processing. The reason being the amount of time taken by the researcher taking a picture and then scan using a phone, which may then drag or slow down the process of attaining a quick usable solution.

5. 5 Future Work

Digitization and advancement in technology is so rapid that every organisation or industry is seeking to improve its operation by means of artificial intelligence. Complex smartphones are being created and the author strongly believe that incorporating such technology with the subject matter can be a great achievement in the health sector. Fusing smartphones and deep learning in screen cancer can reduce cost of acquiring complex hardware for cancer screening at the same time maintaining accuracy of tests.

5.6 Challenges faced.

During the research, the author’s laptop gave up in the closing minutes of the final leg, the LCD got broken and however he resorted to a friend’s laptop to resume the research project. The laptop had little processing which led to delays during the model training processes.

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