MAMMOGRAPHY CLASSIFICATION USING DEEP LEARNING FOR KENYAN CANCER CENTRES

ONYANGO VICTOR ZEDDY'S OCHIENG - 101057

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Date of Submission: May 6, 2021

Declaration

I declare that this project has not been submitted to any other university for the award of Bachelor of Science in Informatics and Computer Science degree.

Admission Number: 101057

Signature .... Date ....

I certify that this work is being submitted for examination with my approval.

Supervisor Name: Mr James Gikera

Signature .... Date ....

Abstract

Breast cancer is a disease where cell in the breast tissue begin to grow out of control. It is the second most common cancer in women after skin cancer (NIC, 2020). Among all other cancers, it leads in incidence and is the 3rd highest cancer in mortality rates. Study shows that breast cancer is detected in the latter stages hence making it much difficult to cure. This shows that early detection of breast cancer is essential to decreasing the disease's mortality rates. Currently, mammography has been termed as the main method for screening in Kenya. However it has two major risks involved:False Negative Results where the tumor is not detected but it exists in the patient's breasts; False Positive Results where the results show that cancer was detected but it is non-existent in the patient's breasts (Ministry of Health, 2018).

This project aims to reduce the prevalence of the risks during screening by developing a neuro-evolved deep convolutional neural network that will be able to differentiate a normal breast, a breast with a benign tumor and a breast with a malignant tumor.

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Abbreviations and Accronyms

AUC - Area Under the ROC Curve

API - Application Programming Interface

BDSS - Breast Cancer Decision Support System

BSE - Breast Self Examination

CBE - Clinical Breast Examination

CBIS-DDSM - Curated Breast Imaging Subset of Digital Database for Screening Mammography

CAD - Computer Aided Design

CLAHE - Contrast-Limited Adaptive Histogram Equalization

CNN - Convolutional Neural Networks

CT - Computerized Tomography

DCNN - Deep Convolutional Neural Networks

DDSM - Digital Database Screening Mammography

DICOM - Digital Imaging and Communications in Medicine

EAR - Ectopic Atrial Rhythm

EKG/ECG - Electrocardiograms

IDE - Integrated Development Environment

JVM - Java Virtual Machine

LMIC - Lower Middle Income Countries

MIAS = Mammographic Image Analysis Society

MRI - Magnetic Imaging Resonance

NIC - National Institute of Cancer, USA

NIRF - Near-Infrared Fluorescence

PET - Post Emission Tomography

ROC - Receiver Operating Characteristic

SE-ResNet - Squeeze and Excitation Residual Networks

SVM - Support Vector Machines

WHO - World Health Organization

Chapter 1: Introduction

1.1 Background

Breast cancer in the world is a serious issue especially in Kenya. According to the National Cancer Screening Guidelines for 2018-2022, this type of cancer has the highest incidence rate and the third highest mortality rate (Ministry of Health, 2018). Available data shows that breast cancer is detected late hence making it difficult to cure or control the disease (Ministry of Health, 2018). The current methodology for breast cancer in Kenya is by using mammography. There are two major risks involved: False Negative Results where the tumor is not detected but it exists in the patient's breasts; False Positive Results where the results show that cancer was detected but it is non-existent in the patient's breasts (Ministry of Health, 2018). Other methods include CBE, Ultrasound, MRI, tomosynthesis, thermography, elastography, PET and BSE and Awareness. However, they are not considered as a replacement for mammography screening in Kenya (Ministry of Health, 2018).

Early detection of the disease is then crucial step in conquering the disease. By screening, we increase the chances of detecting the disease in the early stages thus improving prognosis and eventually decreasing the disease's mortality rate (Ministry of Health, 2018). The use of a deep learning classification model will aid in reducing the mortality rate by increasing the number of cases detected in the early stages of the disease.

1.2 Problem Statement

The existing breast cancer screening methods in Kenya highly depend on the skills of the radiologist to detect the tumor. As a result, there exists risks namely: False Positive Results where breast cancer is detected but the patient does not have it; False Negative Results where breast cancer is not detected but the patient does have breast cancer (Ministry of Health, 2018). This has led to misdiagnosis delayed detection of breast cancer and/or increased cost in both screening and treatment (Gakunga et al., 2019).

1.3 Objectives

The purpose of this study is to develop a neuro-evolved deep learning model for mammogram classification for breast cancer screening in Kenya.

1.4 Specific Objectives

i To research and analyze the current solutions for breast cancer detection.

ii To develop a classification model that can identify differentiate normal breasts from those with benign or malignant tumors.

iii To evaluate the performance of the developed model.

1.5 Research Questions

i What problems are associated with current cancer screening methods?

ii How effective can using deep learning algorithms be in breast cancer detection?

iii How can we evaluate the deep learning algorithm to ascertain that it works?

1.6 Justification

There is need to develop a model that can aid in early detection of breast cancer. This model will assist in reducing false positive and false negative results hence making breast cancer screening much efficient. By being able to detect breast cancer early, the mortality of the disease can be reduced since doctors will have more time to treat it. This may also lead to decrease in costs of treatment in the long run since the disease has been detected early thus treatment can be done in a more efficient way.

1.7 Scope and Limitations

The study focuses mainly on mammography as a breast cancer screening method and attempts to improve its efficiency by the use of image classification. The study focuses on breast cancer detection in Kenya. Its success highly dependable on the source of training data since they have a big in impact on how accurate the model can be (Ragab, Sharkas, Marshall, & Ren, 2019).

Chapter 2: Literature Review

This chapter discusses the different documentations of previous similar projects but with a wider scope. The chapter also focuses on the successes and failures as reported in the documents of study.

2.1 Breast Cancer Screening in Kenya

Under the 2018 National Cancer Screening Guidelines by the Ministry of Health of Kenya, cancer has been termed as the third leading cause of death after infectious and cardiovascular diseases. Breast cancer was reported to be the leading cause of cancer in incidence with 5895 new cases, accounting for 12.5% of all new cancer cases in Kenya(Ministry of Health, 2018). The guidelines also report that breast cancer also accounted for 9.2% of all cancer deaths thereby making it the third leading cause of cancer deaths in Kenya. The reason for the high cancer deaths was attributed to late detection of the disease (Campbell, 2014).

In Kenya, as with the case of many LMICs experience late-stage detection of the disease at which cure is difficult to achieve (WHO, 2017). Additionally, some areas in Kenya have few to zero access to diagnostic and treatment services. A study at Kenyatta National Hospital portrayed this issue whereby 7.4% were diagnosed in tumor stage I, 33.7% in stage II, 29.7% in stage III, and 21% in stage IV with breast lumps being the most common presentation (79.4%), followed by breast pain (26.8%) (Ministry of Health, 2018). There is a projected increase of 35% in the breast cancer incidence by 2025 (Gakunga et al., 2019).

In Kenya, mammography has been stated to be the main breast cancer screening method (Ministry of Health, 2018). Although there are other screening methods like CBE and BSE, mammography, according to the guidelines, has been shown to be the only screening modality that reduces breast cancer mortality. That is because mammography has shown to have an estimated sensitivity of 83% to 95% and a specificity of 95% to 98% (Joy, 1970). A study published on 2019 identified Health System Delays where misdiagnosis was one of the problems they encountered (Gakunga et al., 2019). An example is given of a doctor who misinterpreted a masses in her breast in a mammogram for scar tissues. After a while, the patient developed additional symptoms and went for further testing using MRI, fine needle aspiration and a biopsy. As we can see from the misdiagnosis, the patient incurred additional costs to get her actual diagnosis.

The use of a deep learning model may help reduce the number of false positive and false negative results in diagnosis hence assist decreasing mortality rate. The data stored by the application can also be used for further studies to improve the breast cancer screening and diagnosis.

2.2 Machine Learning Algorithms on Cancer Detection

Machine learning is a branch of artificial intelligence where the program is able to learn from past experience and/or adapt to current change to its environment. One of the application areas machine learning can be used is in cancer detection.

An example is Stanford University's algorithm to detect abnormalities in EKGs. The algorithm was created using a multi-layered CNN and was able to exceed the performance of human cardiologists in identifying heart conditions such as atrial fibrillation, complete heart block, and ectopic atrial rhythm (EAR) (Bresnick, 2017). Such technology can be used in smart watches or any other wearable device to to keep track on at-risk people and alert emergency services to potentially deadly heartbeat irregularities as they're happening. They could also be used in areas where access to a cardiologist is difficult (Kubota, 2018).

Another example is Google's deep learning tool that could detect lung cancer as good as or much better than human radiologists One of the problems the radiologists faced with lung cancer detection was that they would scan through numerous 2D images within a single CT scan and they still couldn't identify the cancer. This research showed that the use of deep learning could significantly improve lung cancer screenings(Kent, 2019).

The above examples show that deep learning has the capability of transforming cancer detection by reducing the prevalence of false positive and false negative results. This supports the aim of using deep learning to aid radiologists detect breast cancer using mammograms.

2.3 Related Applications

The following are examples of related applications that use deep learning to detect breast cancer using various screening methods. They include:

2.3.1 Breast Cancer Histopathological Image Classification Using CNN with Small SE-ResNet Module

This model was built using a convolutional neural network to classify histopathological images. Histopathology refers to the microscopic examination of tissue in order to study the manifestations of disease (*Histopathology*, 2020). It is a widely used screening method for breast cancer detection. The model that was created by the researchers showed a 98.87% and 99.34% for the binary classification and achieve the accuracy between

90.66% and 93.81% for the multi-class classification (Jiang, Chen, Zhang, & Xiao, 2019). Below is an image of the model's architecture.

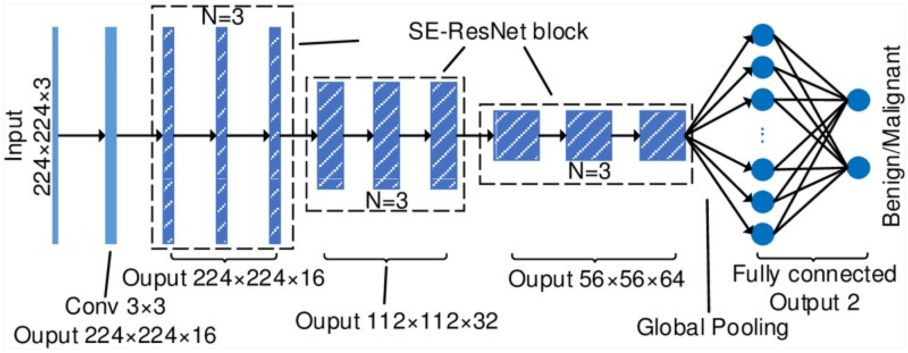

Figure 1: CNN with SE-ResNet Module

Below is the image of the model's performance on differentiating benign tumors and malignant tumors using histopathological images with magnification factors of 40X, 100X, 200X and 400X respectively. The various columns are the the accuracy curve, the loss curve and the confusion matrix (Jiang et al., 2019).

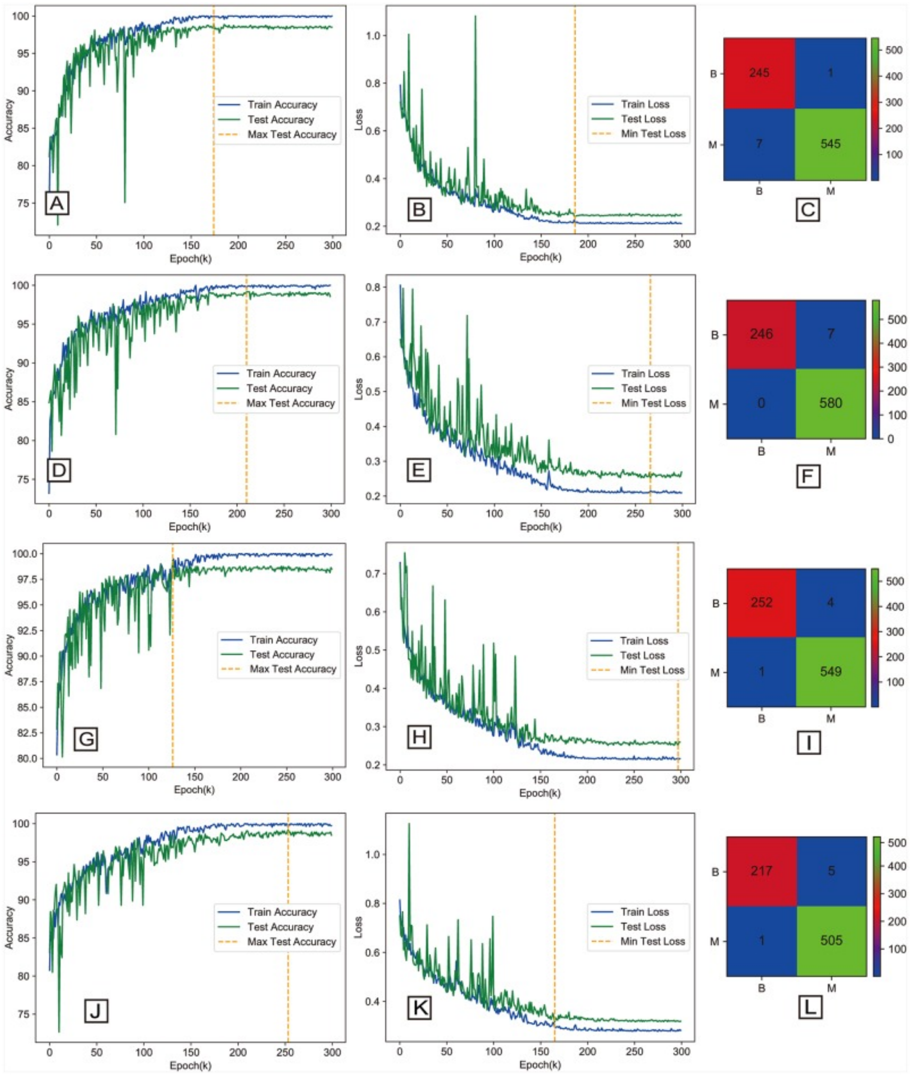

Figure 2: Model's performance on binary classification

The following is a image of the model's performance on multi-classification of the tumors into their sub-types using histopathological images with magnification factors of 40X, 100X, 200X and 400X respectively. The various columns are the the accuracy curve, the loss curve and the confusion matrix (Jiang et al., 2019).

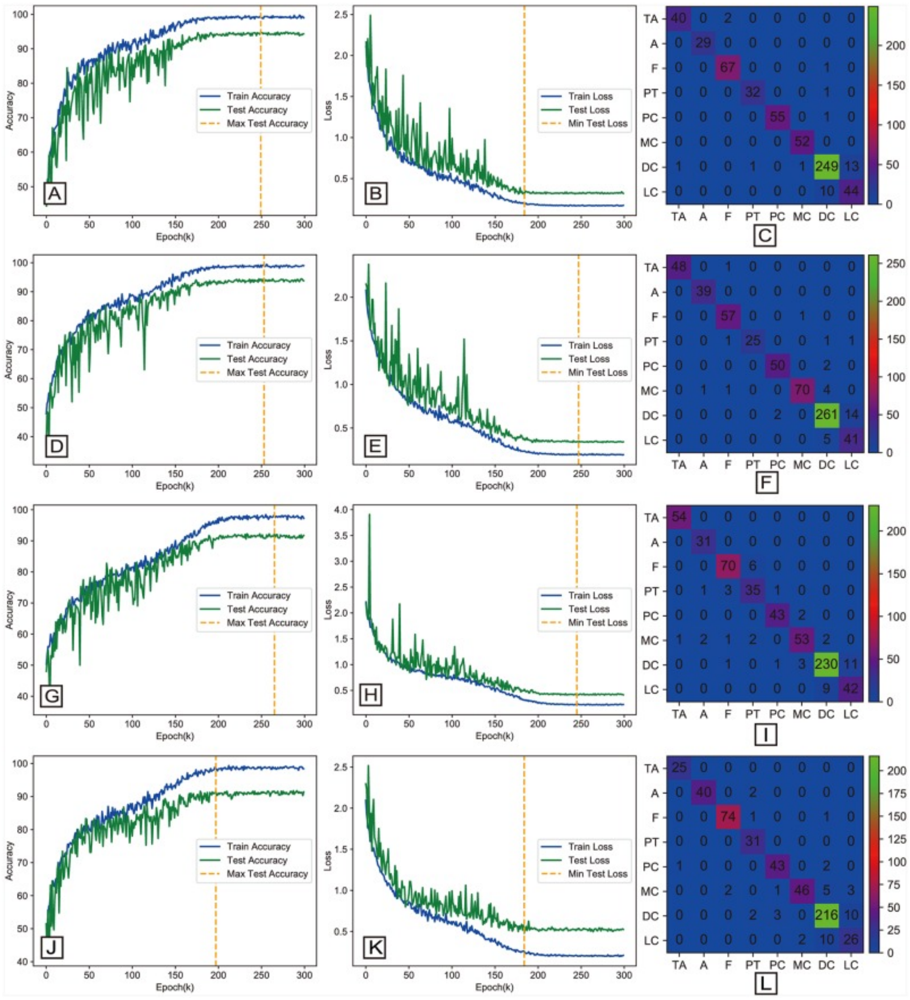

Figure 3: Model's performance on multiclassification of the tumors into their subtypes

2.3.2 Breast Cancer Detection Using DCNN and SVM

This study developed a CAD System that classified bening tumors and malignant tumors using mammograms (Ragab et al., 2019). The DCNN was mainly used for feature extraction. AlexNet, an architecture for DCNNs was used. The features were then transferred to the SVM classification model which increased the accuracy of the model. The DCNN model attained an accuracy of 73.6% using the CBIS-DDSM. In addition the accuracy of the SVM with medium Gaussian kernel function became 87.2% with AUC reaching 94%. Furthermore, the sensitivity, specificity, precision, and F1 score reached 86.2%, 87.7%, 88%, and 87.1%, respectively.%.

The model's architecure and performance is as shown below is a shown below.

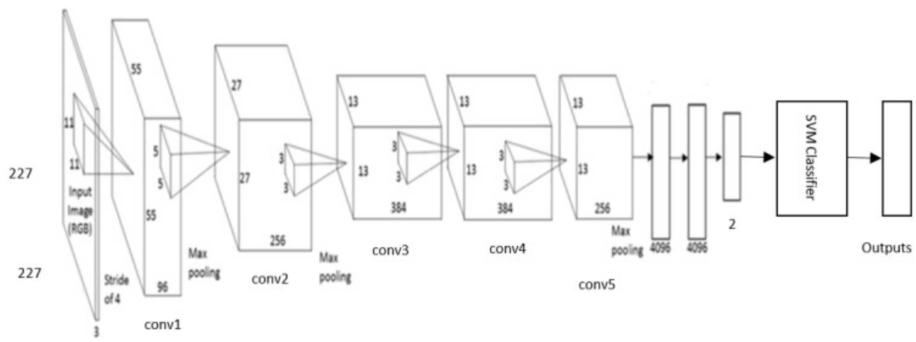

Figure 4: DCNN and SVM Architecture

(Ragab et al., 2019).

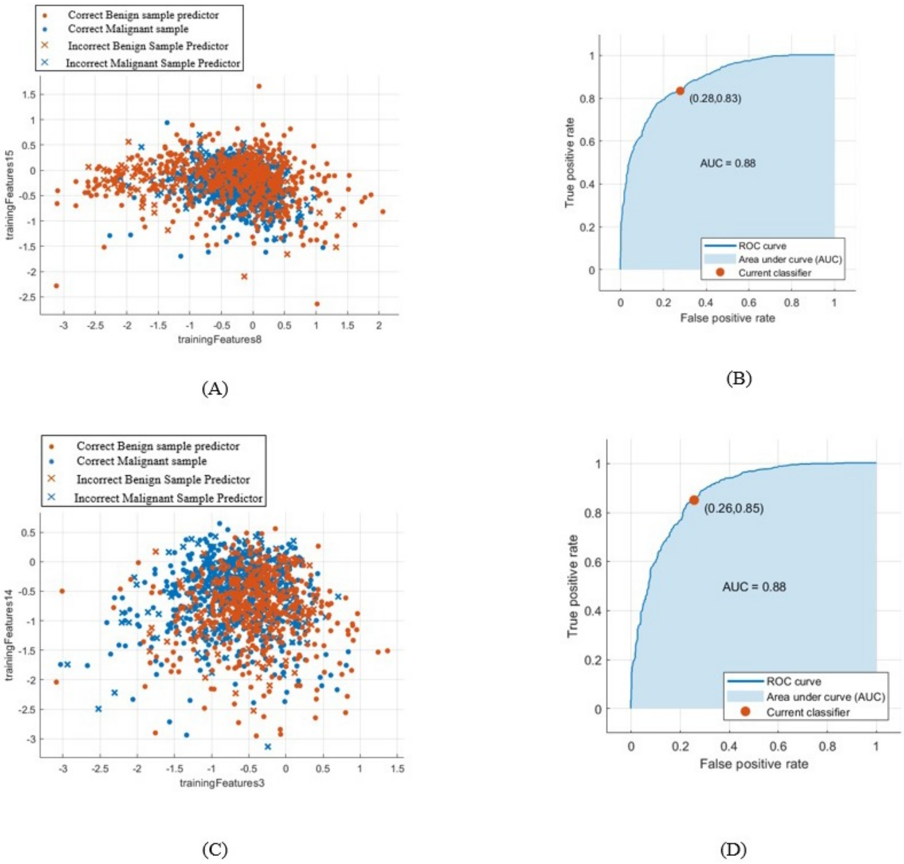

Figure 5: Results of the SVM classifier

2.3.3 Use of Infrared Thermal Imaging and a Deep Learning in Breast Cancer Detection

The research uses Near-Infrared Fluorescence(NIRF) for cancer diagnostics (Mambou, Maresova, Krejcar, Selamat, & Kuca, 2018). IR780phospholipid micelle is used because it has thespecifically for its ability to attach onto tumor cells thus resulting into much detailed images for diagnosis. The researchers used a deep learning model with a SVM for binary classification between healthy and sick breasts. They use a pre-trained Inception V3 model that is modifed at the last fully connected layer in such a way as to obtain a powerful binary classification.

The images below show the distribution of the model's extracted features and the performance of the model on test data.

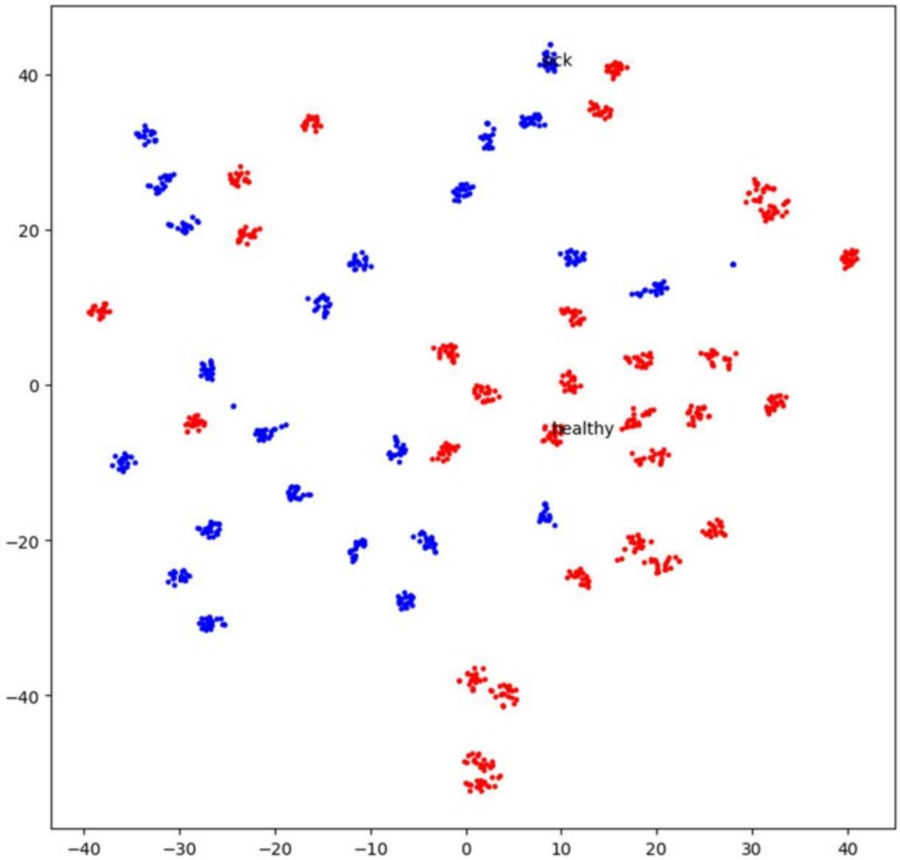

Figure 6: The spatial distribution of the pretrained InceptionV3 model extracted feature.

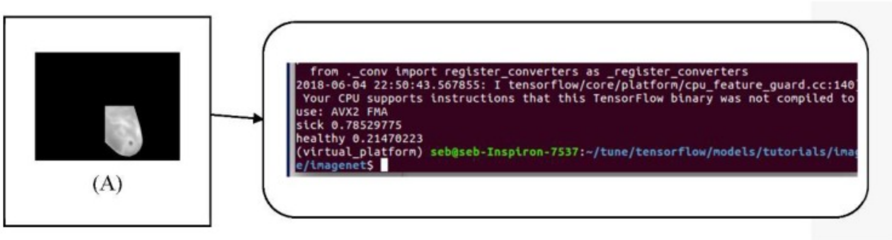

Figure 7: The model classifies the image as “sick” with a confidence of 0.78

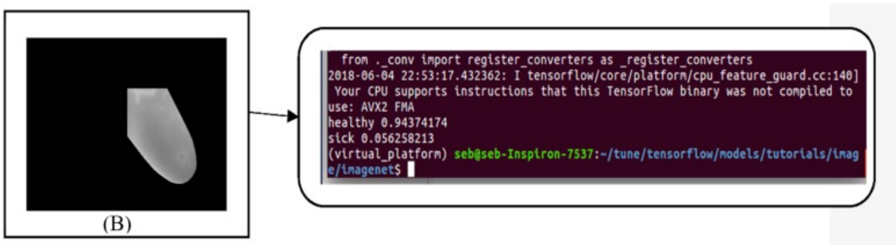

Figure 8: The model classifies the image as “healthy” with a confidence of 0.94.

2.4 Review of Methods used in the past

The solutions discussed in this chapter were successful in the aim of detecting breast cancer. However, some of the models created could only be used for binary classification(benign and malignant tumors) and not differentiate normal breasts with those with tumors in them. Additionally, mammography being the main method of breast cancer detection in Kenya as required by the Ministry of Health in Kenya (Ministry of Health, 2018). As a result, the use of histopathology in Kenya may be quite limited.

2.5 Conceptual Framework

The conceptual framework explains the process under which classification will take place. The mammogram is first enhanced by increasing the contrast and suppress the noise in the mammogram image using the CLAHE algorithm. This makes features in the images easier to perceive by the model. A CNN will be trained using the mammogram images to obtain the optimal model. The features derived from the CNN will be passed to a classifier model for classification of the images into the different classes. The model's performance is then evaluated using the confusion matrix. The conceptual framework is as represented in the image in the next page.

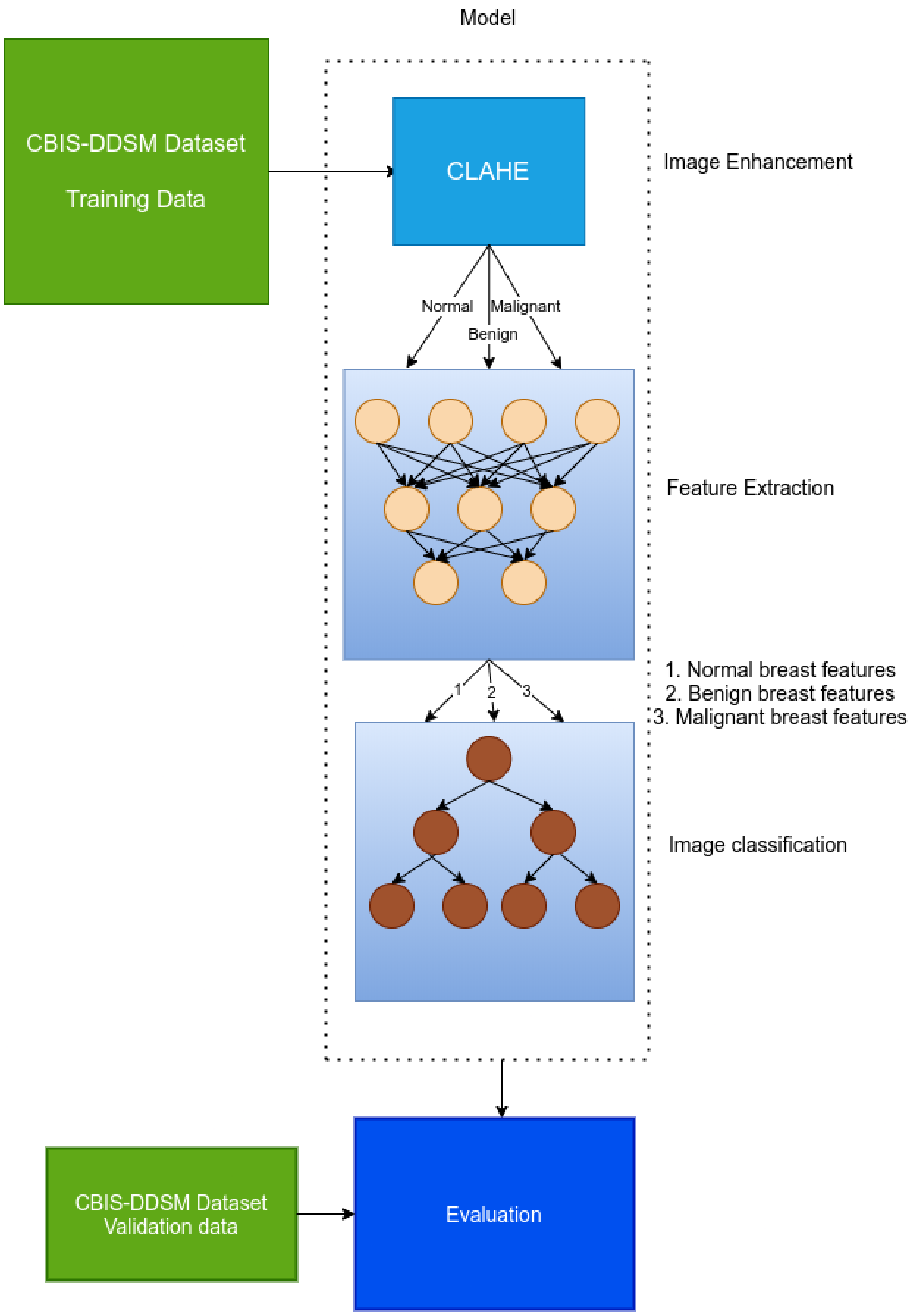

Figure 9: Conceptual Framework

Chapter 3: System Development Methodology

3.1 Introduction

This chapter describes research methods, approaches and designs used in the study and under the guidance of the research objectives in Chapter 1. The study area is that of early breast cancer detection in Kenya. The main objective of the study is to develop a model that will be able to perform multi-classification of mammograms thereby reducing the number of false negatives and false positives in breast cancer detection. To test the applicability of the model, a simple prediction tool will be created to test the usability of the model.

3.2 Research Design

This study will use Rapid Application Development Methodology since the prediction tool in its design is simple. The study will incrementally add new features to the system with an aim to create a more useful tool for detection.

3.3 Data Collection

3.3.1 Primary Data

Also known as raw data, is data collected by the researcher from first-hand sources like interviews, surveys etc. This can either be qualitative or quantitative however the study will focus more on the latter. Qualitative data obtained will aim at getting what kind of features radiologists would expect from such a system.

3.4 Instruments of Data Collection

3.4.1 Document Analysis

This involves reading materials(newsletters, reports, publications), documentation and descriptive statistics related to the study (*Qualitative Data Collection Methods - Research-Methodology*, n.d.). These materials will provide additional information regarding the study that will guide me in the creation of the system.

3.4.2 Mendeley Dataset and Mini-DDSM

The Mendeley Dataset is a resource for use in mammographic research. The resource is a combination of the DDSM, INbreast and MIAS datasets. It contains all three datasets as separate folders and also has them combined in one folder. The images were resized to 227*227 pixels. In total, the folder with the combined dataset had a total of 24576 mammograms comprising of benign and malignant pathologies (Lin & Huang, 2020). The mammograms representing breasts that were okay were obtained from the Mini-DDSM dataset (Lekamlage, Afzal, Westerberg, & Cheddad, 2020). They were 2728 mammograms from the normal class bringing the overall tally to 27304 mammograms.

3.4.3 Data Preprocessing

This step involves all activities done to prepare the data for training the model. The major steps that will be undertaken are image segmentation, histogram equalization and train/val/test split.

3.5 Model Training

Model training will involve provision of the training data into the deep learning model. The model in use will be a CNN with the AlexNet architecture.

3.6 Model Accuracy

The model's performance will then be evaluated using the confusion matrix, loss and accuracy graphs.

3.6.1 Confusion Matrix

Confusion matrix is a 2x2 matrix that compiles the results into 4 classes: True Positive(TP), True Negative(TN), False Positive(FP), False Negative(FN). From the matrix, we can derive information that is helpful ie accuracy, precision, recall and F1 score (*Confusion matrix*, 2020).

Confusion Matrix

	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	True Positives (TPs)	False Positives (FPs)
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)

Figure 10: Confusion Matrix

$$\text{Accuracy}(\text{A}) = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

Figure 11: Accuracy Formula

$$\text{Precision}(\text{P}) = \frac{\text{TP}}{\text{TP} + \text{TN}} \tag{2}$$

Figure 12: Precision Formula

$$\text{F1Score} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} \tag{3}$$

Figure 13: F1 Score Formula which is the harmonic mean of precision and sensitivity

3.6.2 Model Testing

The model will be tested with a test set derived from the mendeley data. Afterwards, the usability of the model will be integrated into a simple prediction tool.

3.7 System Development Methodology

The development methodology that will be used is Rapid Application Development(RAD) that focuses on fast and efficient development of software (Kissflow, 2020). It has 4 phases: Requirements Planning, User Design, Construction and Cutover.

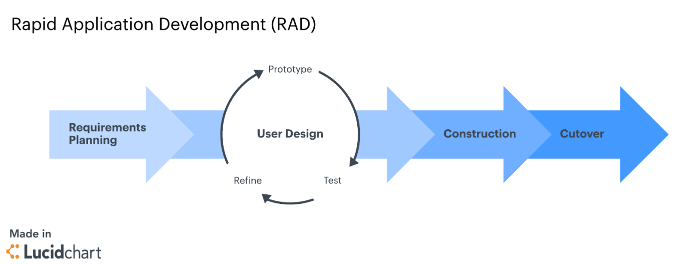

Figure 14: Rapid Application Development(RAD)

3.7.1 Requirements Planning Stage

At this stage, goals are made, expectations of the project are outlined and potential issues are planned for. It also involves to collection of relevant data pertaining the study. In this case, data will be obtained from Mendeley Data and from questionnaires.

3.7.2 User Design

This stage entails the design of the software and the architecture to be used. This will achieved using Unified Modelling Language(UML) diagrams to visualize design of the system. Also data flow, class and sequence diagrams will be used.

3.7.3 Construction

This stage involves the implementation of the solution using the designs from the previous stage. An advantage of RAD is it's flexibility thus changes can be implemented at any time. Java and Python are the main languages that will be used for development. Testing and validation of the model will be done at this stage too.

3.7.4 Cutover

Also known as the transition stage, will involve testing of the tool's functionality using mammograms that aren't from the dataset. It will also involve testing by mammographer. The documentation for prototype users will be at this stage.

3.8 System Development Tools and Technique

The developed tool will be web based to simulate mammogram upload for prediction and results reception. The tools to be used are:

3.8.1 Intellij Community Edition

This is an IDE used for java development created by Jetbrains.

3.8.2 Spring Framework

This is a Java framework for web based development. This will be used to serve the web page to the user and upload the mammogram to the prediction API.

3.8.3 Flask

This is a python framework for creating web based applications. This will be used to create an API for mammogram prediction.

3.8.4 Google Colabs

This is an online python notebook provided by Google. This will be used to host the predictor API.

3.9 Ethical Considerations

The identity of the questionnaire respondents will be hidden hence ensuring proper respondent anonymity, privacy and confidentiality. Full consent will be provided to the respondents before they partake in the study. The questionnaire will avoid any form of deception, exaggeration and bias.

Communication with the respondents will be honest, transparent and voluntary.

Chapter 4: System Analysis and Design

4.1 Introduction

The overall architecture of the proposed system was done by taking into account the mammogram screening process. Diagrammatic representations were created by modelling software to bring out a detailed understanding of each entity. These diagrams explain how the entire environment operates to achieve the required result.

4.2 System Analysis

This section focuses on the requirements achieved, based on the study objectives.

4.2.1 Functional Requirements

4.2.1.1 Mammogram Upload and Preview

The tool should allow the user to upload a mammogram and preview it be for upload.

4.2.1.2 Mammogram Classification

The tool should allow the user to upload the image to the predictor API so as to get the pathology of the mammogram.

4.2.2 Non Functional Requirements

4.2.2.1 Simplicty

The prediction tool has an intuitive design to maximize user experience whilst achieving maximum results.

4.2.2.2 Usability

The tool is designed to enable each functionality can be properly used for mammogram prediction.

4.2.2.3 High Performance

The API is hosted in Google Colabs to ensure high performance of the API for mammogram prediction.

4.2.3 System Architecture

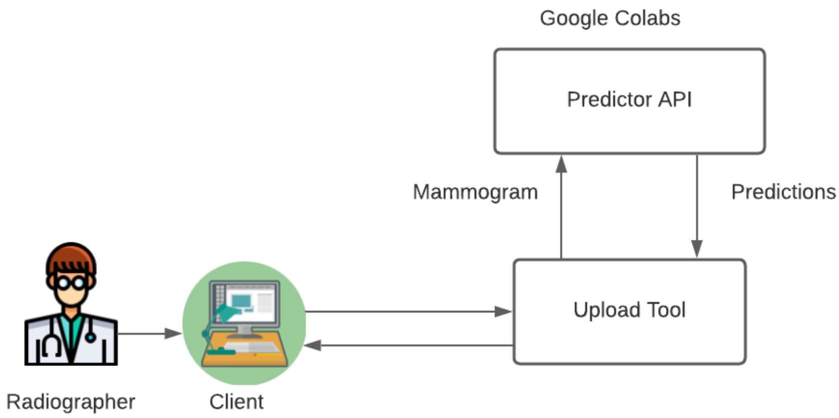

Figure 15: Prediction Tool

The system architecture is as shown in Figure 15. The radiographer begins by accessing the web client. They are served with an upload page. The radiographer uploads a mammogram and previews it before uploading it to the predictor API. The API preprocesses the mammogram, runs an inference on the mammogram and returns the result which are displayed to the radiographer on the web page.

4.3 Diagrammatic Representation of the BDSS

4.3.1 Use Case Description

There are only one key actors which is the the user. The user is a registered radiographer who can both upload a mammogram and view predictions.

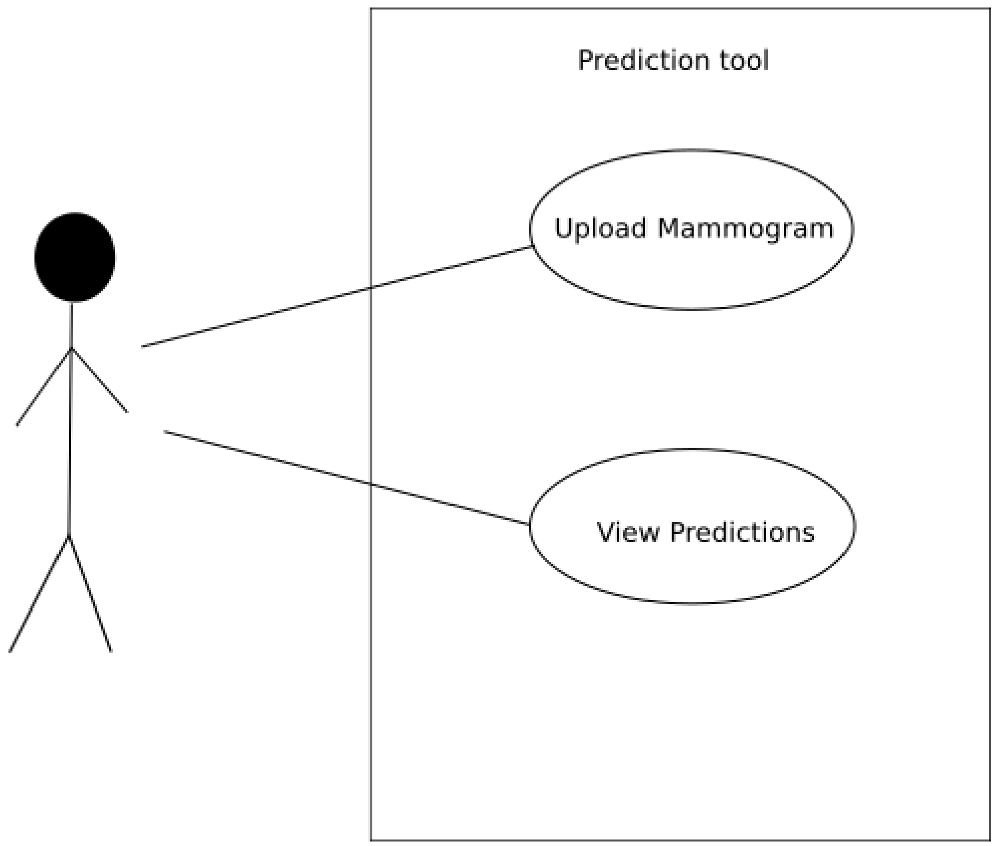

Figure 16: Use Case Diagram

4.3.2 Data Flow Diagram

This is a diagram that presents a visual flow of information within the architecture (Scheel & Foldager, 2015).

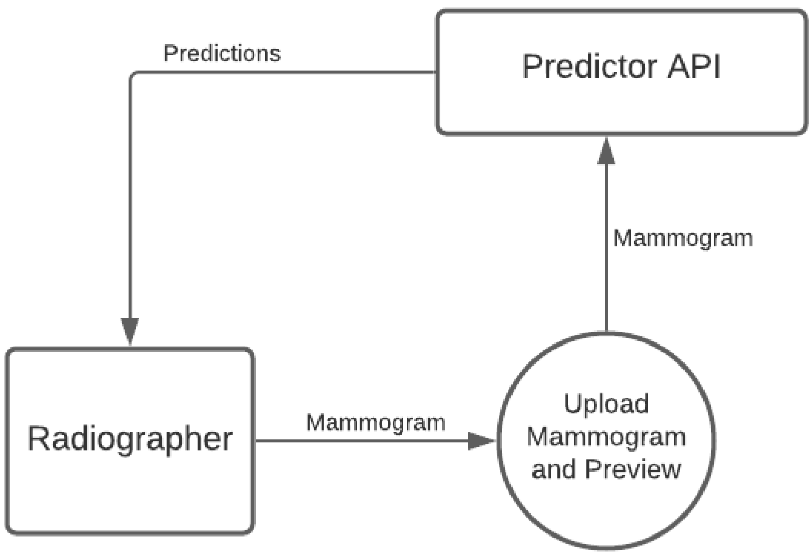

Figure 17: Data Flow Diagram

The user uploads a mammogram and preview it. The user can get the pathology of the mammogram by uploading it to the predictor API. The user is able to receive the results and view them.

4.3.3 Deliverables

The expected deliverables are:

4.3.3.1 User Module

This allows the user to upload mammograms and preview them before upload it to the API.This also allows the user to receive the prediction of results of the model from the API.

4.3.3.2 Final System Documentation

This is a document that elaborates on the training of the machine learning model, development of the prediction tool and any foreseen future works together with recommendations to improve the tool.

Chapter 4: Implementation and Testing

5.1 Implementation

This sections elaborates in detail the development of the machine learning model, development of the user module and its testing phase. The user module is a web application.

5.1.1 Dataset Preparation

The Mendeley Dataset was used for training the model (Lin & Huang, 2020). Several steps were taken to prepare the dataset for training:

5.1.1.1 Image Segmentation

This is the process of partitioning a digital image into different segments/zones (Shapiro & Stockman, 2001). This allows us to obtain the breast image from the mammogram and eliminate unnecessary objects from the mammogram. The simplest form of segmentation is thresholding which involves turning a gray-scale image into a binary image. For this case, Otsu's thresholding was used.

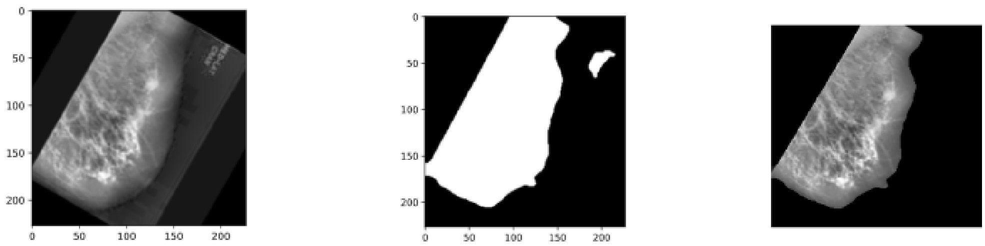

Figure 18: Otsu's Thresholding and Segmentation

Otsu's thresholding is an algorithm that iterates through all possible threshold values as it calculates the pixel's foreground or background variance to identify at which point the sum of foreground and background spreads is at its minimum (Greensted, n.d.). The threshold is afterwards obtained (binary figure in the image above). Edge detection algorithms like dilation is used to optimize separation of the contours. From the threshold we identify the largest contour and from the mask and apply it to our original image to obtain the final outcome on the right.

5.1.1.2 Histogram Equalization

This is an algorithm for improving contrast of an image (*Histogram Equalization*, n.d.). It spreads out the intensity ranges of the image's histogram. The histogram equalization algorithm used was CLAHE.

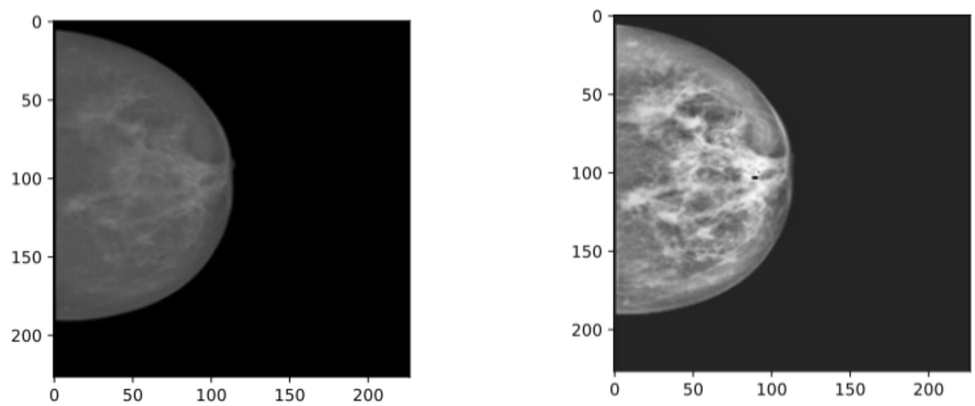

Figure 19: CLAHE

This method computes several histograms each in correspondence to different segments of the image. Afterwards it uses them to adjust the lightness values of the image (*Adaptive histogram equalization*, 2020).

5.1.1.3 Train/Val/Test Split

The dataset was then split into train, test and validation folders using split-folders python module (Filter, n.d.).

5.1.2 Model Training

The model in use was a CNN with the AlexNet architecture. The network has 8 layers: 5 convolutional layers and 3 fully connected layers (Anand, 2019). The summary of the model can be found at the appendix. The model was trained from a Google Colabs notebook.

The model's performance in my opinion is sufficient enough to be used to aid mammographers in decision making. The model was similarly fast in giving predictions thus encouraging its use the more.

5.1.3 User's Module

This module represents a use case under which the model can be implemented. To simulate the process, a simple web based tool was created. The tool's front end is as shown below.

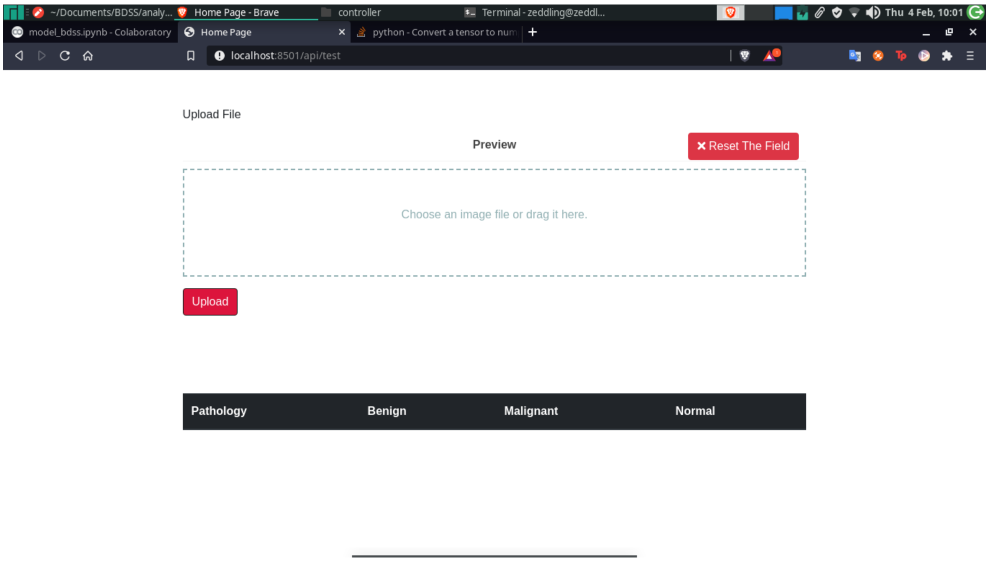

Figure 20: Upload Page

The middle panel allows users to either drag and drop a file or to access they're file system by clicking on it. Once they've uploaded the file, the user can preview the mammogram before uploading it as shown below.

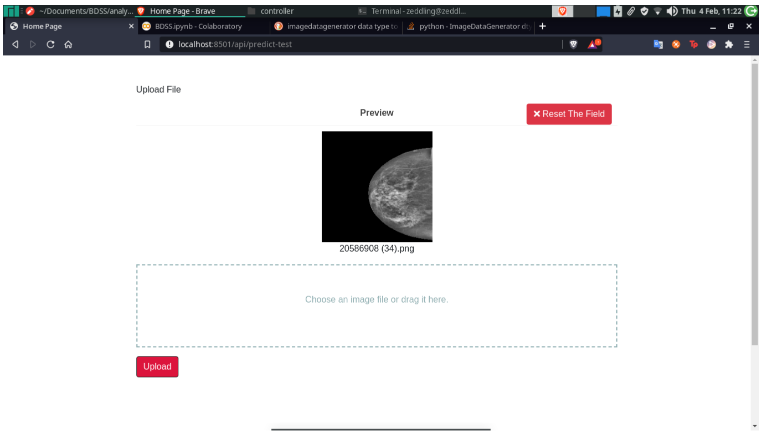

Figure 21: Mammogram Preview

The user can afterwards upload the mammogram to the API via the upload button. Once the model has finished giving inferences, the result is sent back to the web client and displayed to the user via the table as shown below. The pathology together with the confidence levels are sent.

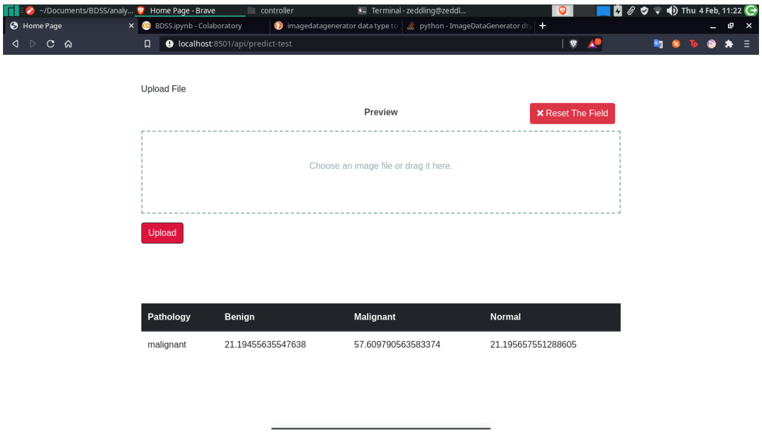

Figure 22: Inference

5.1.4 Predictor API

The Predictor API is of a Flask Framework implementation. By the use of the flask-ngrok python module, the API can be publicly exposed during runtime enabling remote access.

5.2 Testing

Testing was done to ascertain the achievments of both functional and non-functional requirements.

5.2.1 Model Evaluation

The model obtained an accuracy of 42% during training with an F1 Score. The following graphs picture the training performance of the model.

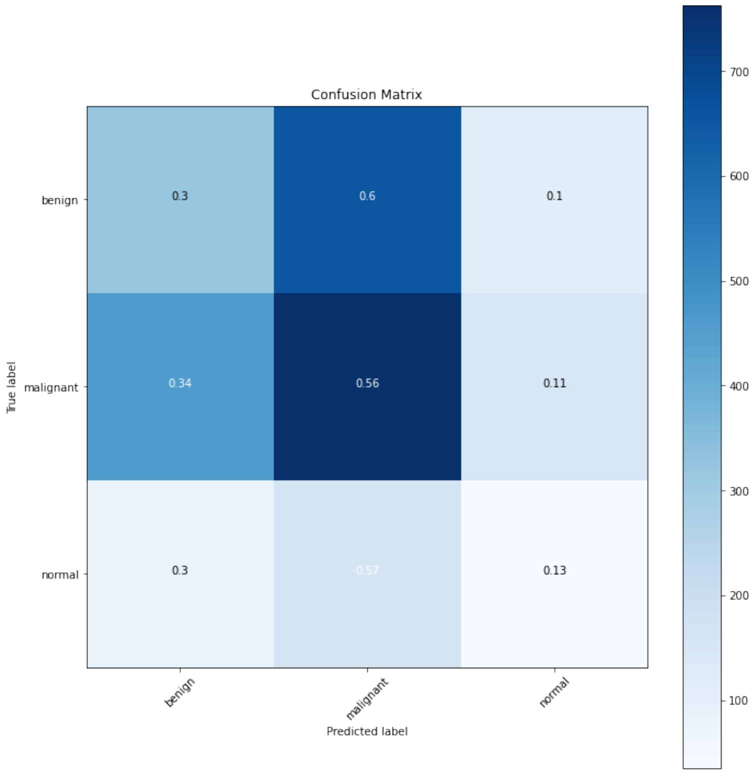

Figure 23: Confusion Matrix

The low performance can be attributed to the unbalanced dataset and lack of enough resources during time of study.

5.2.2 Functional Requirements

The prediction tool allowed the user to both upload the mammogram and preview it before submitting it for inference. The API was able to get the mammogram via a POST request and the response contained the prediction results as required.

5.2.3 Non-Functional Requirements

The prediction tool was designed to match every other file upload design paradigms to give a sense of familiarity while using the tool. This makes the application must simpler to use. The API utilizes Google Colab's GPUs ensuring that the API is fast in giving predictions.

Chapter 6: Conclusion, Recommendation and Future Works

6.1 Conclusion

As a result of the number of rising cases of breast cancer in Kenya, this project aimed at: researching on the state of breast cancer detection in Kenya, more so in Nairobi, research on available models used in breast cancer detection designing a multi-classification model to aid in reducing false negatives and false positives and testing the model.
The AlexNet CNN can be able to classify the mammograms once trained with a balanced dataset.

6.2 Recommendation

The model is aimed to assist in early breast cancer detection. The adoption of the model by hospitals and cancer research centers can assist them in expanding to rural areas. By using the API, they can be able to make it possible for women in the rural areas to get breast cancer screening results faster and in the long run cheaper since they won't have to come all the way in Nairobi.

6.3 Future Works

In the future, machine learning models like YOLO can be incorporated into screening machines to provide real-time detection of abnormalities in the breast tissue and much more accurately. Similarly, deep learning models like the solution used by this project can be used in hospitals to give instant results to the patient during screening.

Deep learning can also be used to create other methods of breast cancer detection that may be cheaper than using mammograms. An example is like in prostate cancer detection where a group of scientist from the Korean Institute of Science and Technology were able to detect prostate cancer using urine and machine learning (Kim, 2021). Similar methods may be implemented as such with the aid of deep learning models.
An imagenet like database for cancer images can be created so as to enable training of deep learning models to identify different types of cancers.

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Appendix

AlexNet Architecture

```
Model: "AlexNet"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 55, 55, 96)        34944
_________________________________________________________________
activation (Activation)      (None, 55, 55, 96)        0
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 27, 27, 96)        0
_________________________________________________________________
batch_normalization (BatchNo (None, 27, 27, 96)        384
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 17, 17, 256)       2973952
_________________________________________________________________
activation_1 (Activation)    (None, 17, 17, 256)       0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 8, 8, 256)         0
_________________________________________________________________
batch_normalization_1 (Batch (None, 8, 8, 256)         1024
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 6, 6, 384)         885120
_________________________________________________________________
activation_2 (Activation)    (None, 6, 6, 384)         0
_________________________________________________________________
batch_normalization_2 (Batch (None, 6, 6, 384)         1536
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 4, 4, 384)         1327488
_________________________________________________________________
activation_3 (Activation)    (None, 4, 4, 384)         0
_________________________________________________________________
batch_normalization_3 (Batch (None, 4, 4, 384)         1536
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 2, 2, 256)         884992
_________________________________________________________________
activation_4 (Activation)    (None, 2, 2, 256)         0
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 1, 1, 256)         0
_________________________________________________________________
batch_normalization_4 (Batch (None, 1, 1, 256)         1024
_________________________________________________________________
flatten (Flatten)            (None, 256)               0
_________________________________________________________________
dense (Dense)                (None, 4096)              1052672
_________________________________________________________________
activation_5 (Activation)    (None, 4096)              0
_________________________________________________________________
dropout (Dropout)            (None, 4096)              0
_________________________________________________________________
batch_normalization_5 (Batch (None, 4096)              16384
_________________________________________________________________
dense_1 (Dense)              (None, 4096)              16781312
_________________________________________________________________
activation_6 (Activation)    (None, 4096)              0
_________________________________________________________________
dropout_1 (Dropout)          (None, 4096)              0
_________________________________________________________________
batch_normalization_6 (Batch (None, 4096)              16384
_________________________________________________________________
dense_2 (Dense)              (None, 1000)              4097000
_________________________________________________________________
activation_7 (Activation)    (None, 1000)              0
_________________________________________________________________
dropout_2 (Dropout)          (None, 1000)              0
_________________________________________________________________
batch_normalization_7 (Batch (None, 1000)              4000
_________________________________________________________________
dense_3 (Dense)              (None, 3)                 3003
_________________________________________________________________
activation_8 (Activation)    (None, 3)                 0
=================================================================
Total params: 28,082,755
Trainable params: 28,061,619
Non-trainable params: 21,136
_________________________________________________________________
```

Figure 24: AlexNet

Gantt Chart

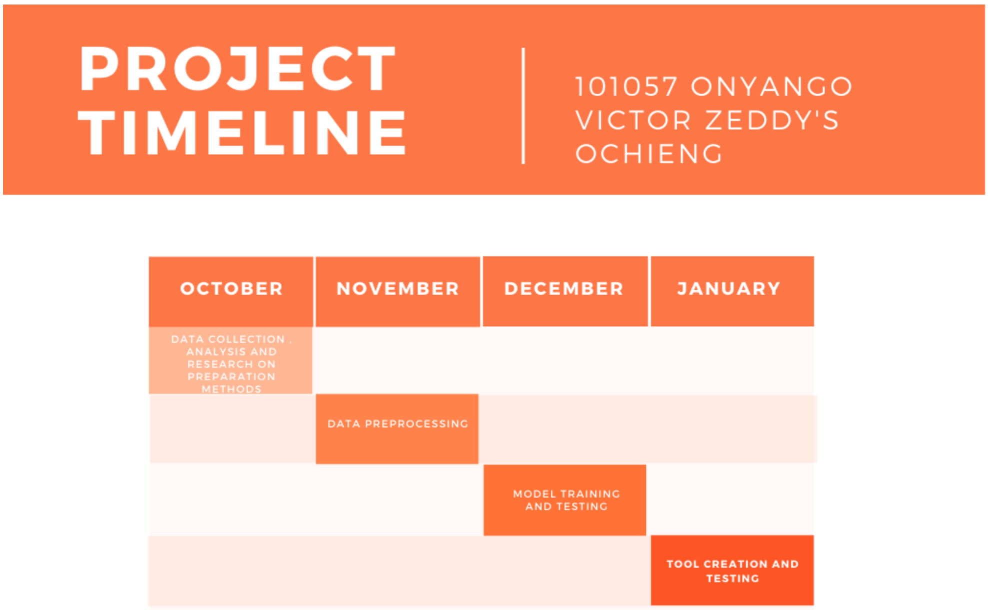

Figure 25: Gantt Chart