MammoCareAI:Development of Breast Cancer Detection and Risk Prediction System Using Convolutional Neural Networks.

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APPROVAL PAGE

This research, titled "**MammoCareAI:Development of Breast Cancer Detection and Risk Prediction System Using Convolutional Neural Networks.**
" has been assessed and approved by the Department of Computer Science and Mathematics Committees in the Faculty of Natural Sciences and Environmental Studies, Godfrey Okoye University, Enugu, Nigeria.

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CERTIFICATION

I certify that I completed the research included therein and that it was primarily based on my observations and investigation. Consequently, I will fully accept the University's decision if I am found to have cheated on the assignment.

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DEDICATION

First of all, I dedicate this work to God almighty for His grace, wisdom, strength and unfailing direction. This work is dedicated to my beloved parents, Mr. and Mrs. Felix Azua, for their support, love, encouragement, sacrifices, and prayers throughout my studies. A special thanks also goes out to my best friend, Miss Kyocher Victoria whose support, encouragement and faith in me inspired me to strive beyond my boundaries. This work is dedicated to my very good friend, Opiah Believe Edmond, whose encouragement and friendship helped sustain me during the course of this project.

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Abstract

Cancer of the breast has contributed to most cancer deaths among women all over the world, which is why there is a significant emphasis on early detection of breast cancer and on the ability to accurately assess a woman's risk of breast cancer. In this study, we sought to create a breast cancer detection and risk prediction system using CNNs to assist in the early diagnosis of breast cancer and in the development of a clinical decision regarding a patient's treatment. The initial phase of the study was to identify the major risk factors linked to the development of breast cancer, followed by the gathering of enough quality dataset, which comprises both benign and malignant breast cancer cases. This dataset served as the foundation for analysing the relationship between identified risk factors and breast cancer occurrence. The data preparation phase included data cleaning, normalising, and transforming the data into a format appropriate for training the CNN model. Next, we created the CNN model that could learn the discriminative characteristics of the benign and malignant breast cancer cases and trained it to detect the presence of these characteristics. After the model was trained, we created a web-based user interface to ease the identification of risk and the practical use of the predictive model. Lastly, we evaluated the performance of the predictive model using multiple metrics such as accuracy, precision, recall, F1-score, specificity, confusion matrix, and Receiver Operator Characteristic (ROC) curve. The results obtained after model evaluation demonstrate that the proposed model performed exceptionally well in breast cancer classification, as it achieved an accuracy of 94.12%, precision of 93.10%, recall of 95.29%, F1-score of 94.19%, specificity of 92.94%, and an Area Under the Curve (AUC) value of 96.87%. The results confirm the model's strong ability to accurately distinguish between different breast cancer classes, which makes it a reliable tool for prediction and classification tasks. The developed system provides an effective and reliable tool, which will be employed in order to carry out breast cancer detection and risk prediction accurately, as well as the potential to support healthcare professionals in enhancing early diagnosis and improving patient outcomes.

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CHAPTER 0NE

INTRODUCTION

1.1 Background of the Study

Breast cancer claims about 43,000 lives a year across the continent, according to the American Cancer Society. In the world today, breast cancer is known to be a very rampant disease among women in society. It is among the contributors to the mortality rate for women, and therefore, it is a global concern. This problem has affected a lot of women in society and has even resulted in the cutting of the breast or, in worst cases, death because it is not detected on time. Breast cancer can be divided into non-invasive and invasive. Non-invasive refers to when the cells are contained within the breast ducts and not spreading into the surrounding tissues, as seen in Ductal Carcinoma in Situ (DCIS). African breast cancer experts say much of that high mortality rate comes down to low awareness among the public, a lack of diagnostic equipment, limited screening and delaying seeking treatment at hospitals (Anyigba et al., 2021).

Although breast cancer is still a very serious concern for female health around the globe and continues to be the number one cancer diagnosed in women today, over 2 million new breast cancer cases were diagnosed globally in 2020 according to Sung et al. (2021). Furthermore, the World Health Organisation in 2021 states that breast cancer is now ahead of lung cancer as the most diagnosed cancer worldwide and contributes to approximately 685,000 deaths each year. The burden of breast cancer tends to be highest in lower-middle income countries where the health care infrastructure is inadequate, there is limited access to screening, and diagnoses are often delayed, resulting in poorer outcomes and higher mortality rates (Bray et al., 2018). Despite improvements to breast cancer treatment and management over time, the odds of surviving breast cancer are still primarily dependent on the stage at which the cancer is detected. For example, studies show that the five-year survival rate may be as high as 99% when breast cancer is detected early on but will drop to approximately 29% if breast cancer has spread to other sites in the body. The American Cancer Society (2022) also highlighted that insufficient awareness, delayed health-seeking behaviour, and inadequate diagnostic facilities in some regions continue to affect the ability of detecting breast cancer early and effective management. In Nigeria, for instance, there just aren't enough radiologists and oncologists for the population.

Standard techniques used to diagnose breast cancer, like mammography and ultrasounds, depend on access to imaging equipment and trained specialists to interpret the images (Gerami et al., 2022). Such resources are also scarce and not equitably distributed across Nigeria. Many women do not have access to regular screening, meaning they are diagnosed late and their clinical outcome can be variable. In places where screening is available, reading the images can be cognitively challenging and time-consuming, vulnerable to fatigue and human error (Adeleye et al., 2023).

Breast cancer has been the reason for the death of many women in the world and early detection of cancerous cells is necessary to reduce the rate of death, have more survivors and also minimize the rate at which hospital bills are been paid and with this proposed research the percentage of how cancerous the cell is will also be gotten this way there is lack of misdiagnosis. After going through so many research papers, it has been proven that the integration of AI in healthcare technologies has helped in the enhancement of treatments, and predictive results are quite accurate (Ding et al., 2021). New technologies integrate machine learning models that have been trained with several datasets to achieve high accuracy in the predictive results, or rather, recommended results are provided. The advent of Artificial Intelligence (AI), and in particular deep learning, has huge potential to help address some of these challenges. In particular, Convolutional Neural Networks (CNNs) have shown impressive performance in automated analysis of medical images by extracting salient features from images and classifying them into disease categories with high accuracy (Mienye et al., 2025). Yet the potential for CNN-based systems to make classification errors underscores the importance of careful implementation, including good design, iteration after validation, and contextually aware decision-making.

To address these issues, we propose MammoCareAI: Breast Cancer Detection and Risk Prediction System. MammoCareAI uses state-of-the-art Convolutional Neural Networks (CNNs) to assist in early detection and prevention of breast cancer. The system combines analysis of medical images with non-imaging risk factors, such as genetics, body mass index, diet, exercise levels and hormonal profile. MammoCareAI has set out to provide a much-needed easy access, smart decision-support tool for the Nigerian and larger African health care communities.

1.2 Problem Statement

Breast cancer poses a significant burden in Nigeria and indeed in Africa, where a vast majority of cases are diagnosed at late stages. This is due to low awareness and lack of screening, inadequate diagnostic facilities, and poor healthcare infrastructure. As a result, cancer survival in much of the developing world is still far below that in developed countries. Breast cancer is still a major public health issue, and lowering death rates and improving treatment outcomes are largely dependent on early detection. The accessibility and reliability of some of these existing models remain an issue. The study will address the following:

i. Falsified datasets: Some of the currently existing cancer detection systems are trained using falsified datasets from unverifiable sources.

ii. Reducing False Positives: Current breast cancer screening methods, including mammography, often produce false-positive results, which reemphasise the challenges associated with current risk assessment practice in Nigeria, which uses manual clinical assessment. This is prone to error and is hindered by the lack of oncologists and radiologists in the country. As a result, many women present late at hospitals, when the treatment options available to them are less effective.

iii. For one, there is no digital system that is directed at early breast cancer risk prediction even before the onset of symptoms, and most existing systems are hospital-centric and not accessible to the population, do not account for hereditary and lifestyle risk factors together and provide contextual health, educational and preventive information for African women.

1.3 Aim and Objective of the Study

This study aims to develop a Breast Cancer Detection and Risk Prediction System Using Convolutional Neural Networks. The specific objectives of this study are to:

1. Identify risk factors associated with breast cancer in order to collect and preprocess the relevant data.
2. Train the model with the breast cancer dataset for efficient breast cancer detection to scale the diagnosis of cancer.
3. Design a user-friendly web-based platform for cancer risk identification
4. Assess the model's performance through multiple evaluation metrics, and develop a software application to facilitate practical deployment

1.4 Significance of the Study

The significance of this study, which is about the detection of breast cancer using machine learning techniques, is multifaceted and therefore spans across different areas, including the following:

i. Reduction of healthcare burdens: With early and accurate detection, healthcare systems can reduce the burden of costly treatments associated with late-stage breast cancer.

ii. Improved Diagnostic Accuracy: The hybrid machine learning model developed in this study has the potential to significantly improve diagnostic accuracy by combining the strengths of multiple algorithms. This leads to a better and reliable result in the detection of breast cancer, which will minimize the rate of deaths or false treatments

iii. Enhanced Clinical Decision-Making: This hybrid machine learning system was built to have the ability to be a healthcare decision support tool that helps healthcare professionals to have an idea of how cancerous the cell is after providing a mammogram image. With this at hand, there will hardly be cases of misdiagnosis, as it gives the healthcare professional a clear view of the cancerous cell.

iv. Advancement of Hybrid Machine Learning Techniques: This research work helps in contributing to the ongoing research on hybrid machine learning algorithms, which therefore shows the efficiency and effectiveness in complex healthcare applications. The focus is on early breast cancer detection. The research shows that using and combining multiple machine learning algorithms along with a deep learning model, which was used for image analysis, produces a much better performance than using a single machine learning algorithm.

1.5 Scope of the Study

The study focuses on developing a deep learning algorithm for the detection of breast cancer, with an emphasis on improving accuracy, reducing false positives and negatives, and making the model clinically applicable.

Important areas consist of the following:

i. Data collection: The study will include the gathering of datasets, including mammograms, ultrasound, and clinical records.

ii. Feature Selection and Model Development: The study will focus on identifying and extracting informative features from medical images and other data sources.

iii. Model Training and Evaluation: The developed models would be trained on labeled datasets to learn patterns and relationships between input features and cancer outcomes.

1.6 Limitations of the Study

Limitations to this study include:

1. Interrupted power supply: While building the system, sometimes there might be a power outage for probably two days or more; this slowed down the process of building the system.
2. Slow Internet connection: The software and systems used in this project relied heavily on having access to the internet. Because of this, internet outages and slow connections sometimes delayed the project and made it difficult for the researcher to work effectively.
3. Image Limitations: The accuracy of the CNN model's predictions is influenced by many factors, including the quality, clarity, and consistency of the images used for prediction. The large variation in the images' resolution, lighting, and overall appearance means that these variables also affect model accuracy.

1.7 Operational Definition of Terms

Artificial Intelligence (AI): Artificial Intelligence is a branch of computer science which focuse on the development of computer systems that are capable of performing tasks which before will demand or require human intelligence. Examples of such tasks include learning from past experiences, identifying patterns, solving complex problems, making decisions, and understanding information in order to achieve specific objectives.

Breast Cancer: A malignant disease originating from abnormal cell growth in the woman's breast tissue.

Convolutional Neural Network (CNN): A deep learning model designed for pattern recognition and predictive analysis.

Cancer: This refers to a disease that causes the uncontrollable growth of cells in the body, and leads to them spreading to other parts of the body

Cancer Progression: the sequential stages of tumor development and growth, including initiation, promotion, invasion, and metastasis.

Chemotherapy: This refers to a treatment for cancer that involves taking drugs to restrict the spread or kill the cancerous cells in the body.

Genetic Mutation: This refers to the alteration of how the gene works due to a permanent change in DNA

Immunotherapy: This refers to a treatment for cancer that makes the immune system recognize and attack the cancerous cell

Metastasis: This refers to the process by which cancerous cells move from the original part of the body and start spreading to other parts.

Model: This refers to a mathematical representation that is trained with data to follow a specific pattern and also predict or recommend various things.

Treatment Optimisation: This refers to a process of designing or using various methods to ensure that a better result is achieved after the treatment has been administered.

Precision medicine: This refers to the innovative procedure taken in the healthcare industry to administer treatment to a patient based on the predicted risk of that disease or other factors, either generic or general.

Risk Prediction: Estimation of an individual's likelihood of developing a disease based on multiple factors such as hormonal imbalance and heredity.

Tumour: This is also known as a neoplasm. It refers to abnormal tissues that are formed when a cell is growing and divides more than it is supposed to.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter of this work of research, however, stands to explore the rising topic of hybrid machine learning-based breast cancer detection. It emphasizes the ability of the method to examine datasets that are in the form of large-scale which includes the data of genetics, medical records and healthcare pictures. However, by discerning intricate patterns and subtle anomalies indicative of breast cancer, these algorithms offer the promise of more accurate and timely detection, thereby improving patient prognosis and survival rates.

This chapter reviews the relevant and existing literature on breast cancer detection, focusing on traditional methods, machine learning applications, and a major focus on hybrid machine learning techniques. The chapter is broken into two major parts: theoretical background and a review of related studies done by different authors.

2.2 Theoretical Background

Cancer is a disorder in which the cells of the body that are aberrant proliferate and spread all around the body. Sometimes, the growth of these cells that can't be controlled results from the mutation of genes. This may occur because of some changes in some factors, including environmental, chemical, or physical elements. However, these cells begin to proliferate uncontrollably and, as a result, keep producing more cells that are living than the ones that are dying. Thereby leading to the accumulation of cells that are known as tumors. Moreover, it is important to note that the early stages of cancer are more amenable to treatment, whereas the later-stage tumors are extremely difficult to cure (Seid and Yesuf, 2019).

However, the early stage of malignancies is more amenable to treatments, whereas later-stage cancers are typically very difficult to treat. In many industrialized nations, cancer has become the primary cause of mortality that are related to disease among human beings. Moreover, in the practice of medicine, the classification of cancer is based on clinical data that is histological, which can lead to conclusions that are inaccurate and misleading. The level of expression of thousands of genes in a combination of cells can be determined simultaneously using the DNA microarray, which is very helpful.

Subsequently, accurate cancer prediction and diagnosis have been achieved by the application of DNA microarray technology. Gene expression profiles combined with molecular-level diagnostics can provide a methodical and precise way of classifying cancers. In the same vein, accurate tumor classification is crucial for cancer treatment. However, many academics have been examining the issues of classifying cancer while making use of data mining techniques, statistical methods, and machine learning algorithms to effectively evaluate this data because gene expression data typically consists of a large number of genes (Han and Kamber, 2010)

Breast cancer, for years now, has been a major worldwide health concern. It is a life-threatening disease affecting women worldwide. Considering this, the only key to a successful course is identifying it early enough, because it has the potential to completely transform the procedures of screening.

2.2.1 Machine Learning (ML) and Image Processing Techniques

A. Machine Learning Techniques

ML is a branch of artificial intelligence that deals with the automatic learning of data by systems to make decisions and make recommendations with little intervention by humans It also identifies patterns in large datasets that are very difficult to identify, or noisy data sets that are noisy. However, medical software, especially the ones that rely on intricate proteomics and genomic data, is the one that is especially well-suited to these qualities.

However, during the classification stage, the features of the texture of the optimal subset, which are chosen for machine learning modelling, are used to classify the patterns of the region of interest. These, therefore, are the abnormalities that are present in breast tissue, either benign or malignant. Moreover, by using a combination of the chosen characteristics and confidence policies, a classifier that is trained on known anomalies (mass lesions and microcalcifications/MCCs) stands to determine which of the ROI is malignant or benign (Duda et al., 2003).

Support Vector Machines:

Support vector machines (SVMs) are the most potent classification techniques that are available today in terms of prediction accuracy. But because it makes use of supervised learning, it finds the best hyperplane to divide two sample classes. It also makes use of kernel functions to separate and present the input data into a higher-dimensional space to achieve a better distribution of data. However, it has grown to be so reliable not although it is relatively a recent technique that is used for classification and prediction.

K-Nearest Neighbor (KNN):

The K-Nearest Neighbor (KNN) is predicated on the idea that instances in a dataset will typically be found nearby other instances with comparable characteristics. But if a classification label is applied to an instance, the class of the closest neighboring instance can be used to calculate the value of the label of an instance that is unclassified. However, unknown patterns are distinguished by the use of the K-nearest neighbor (KNN) classifier based on how similar they are to examples that are already known.

Neural Network:

A neural network is one of the most popular AI methods. It can acquire the knowledge of a data set and create matrices that are weighted in order to show the patterns of learning. On the other hand, the artificial neural networks or ANNs, which are nonparametric algorithms to recognize patterns in which general rules from, by learning from data that are real or examples that are passed to it.

However, this approach is preferable in situations where the choice of rules is ambiguous and clear knowledge of the probability density functions controlling sample distributions is lacking. Three essential features of artificial neural networks are nonlinear processing, local operations, and distributed representation.

1. Random Forest:

Random forest is an algorithm for supervised learning. The set consists of several Decision Trees or which are hierarchical in structure. It appears to be made up of branches that divide the choice toward the leaf nodes and nodes that indicate specific conditions on a given set of attributes. The class labels are determined by the leaf. Recursive partitioning or conditional inference trees can be used to create decision trees. The methodical procedure through which a Decision Tree is created by dividing or leaving every other node whole is known as recursive partitioning. We can state that the source set is divided into different subsets that are according to the test value of an attribute, which is how the tree is learned. However, the replication comes to a halt when every value that is of the target variable in the subset at a node is the same.

Therefore, a statistical method called Conditional Inference Tree employs some sort of nonparametric tests as splitting criteria. These splitting criteria are then adjusted for multiple testing to prevent overfitting. Random Forest can deal with continuous, categorical, binary, and missing values because it is well-suited for high-dimensional data modeling. Moreover, for data sets that are large, the size of the trees may require a significant amount of memory, thereby resulting in adjusting the hyperparameters, which is necessary because it tends to overfit (Arpita and Ashish, 2017).

2. Logistic Regression:

When you use linear regression to make predictions about a dependent variable, you cannot simply use the independent variable and the resulting linear regression hyperplane. This is why logistic regression is typically used to analyze categorical data. Logistic regression will create a probability of the outcome of an event (categorical). Logistic regression predicts a category, or "class", of data (therefore, it is used for classification) rather than predicting a continuous variable. The logistic regression will convert the independent variable into a probability of occurrence regarding the dependent variable. The final probability of an event occurring is always expressed as a value between 0 and 1; this is done using the sigmoid function. Logistic regression uses a specific set of parameters that define the probability distribution of a sample, and create new classification samples using either continuous or discrete measurements. Logistic regression has the advantage of having the ability to return probabilities of possible outcomes to new samples, as well as classification accuracy of the sample. If there was linearity between the two (independent and dependent) variables, there is a disadvantage to the logistic regression as compared to the linear regression.

3. Naïve Bayes:

The classifier of Naïve Bayes is an algorithm that is used in supervised learning and is used for classification. It is one of the machine learning methods that his most effective and straightforward that is used now. Most importantly, this model presumes that every predictor, or feature, is not dependent on each other, which is very hard to be the case in reality. Therefore, this restricts the usefulness of the algorithm to the scenarios in the real world. Also, the "zero-frequency problem" that this approach encounters is when it gives a categorical variable, which has no probability, whose category in the dataset that is used for testing wasn't included in the dataset that is used for training. We can therefore use a smoothing technique to get around this problem. Furthermore, a disadvantage of Naïve Bayes is that it requires data sets that are large to be able to achieve the best amount of accuracy.

4. Decision Tree:

Decision Tree is one of the machine learning algorithms that are the most popular ones. It has been popular due to its ease, readability, and ability to handle numeric as well as categorical data. It works through subdivision of the data set into several but easily manageable sets with respect to the nature of individual input components. These divisions create a tree-like structure which instructs the process of prediction guided by a series of conditional choices.

2.2.2 Deep learning

Deep learning is particularly powerful in managing large, unstructured datasets such as images, audio, and time-series sensor data. With an example of the detection of breast cancer, decision trees will be based on a set of attributes of the diagnosis, which will include the size of the tumor, shape of the cells and the texture of tissue in order to decide whether a specific case belongs to the benign or malignant category. With every step the algorithm goes through these features, it becomes more and more a localized constant that allows it to make its ultimate prediction. Although this method is quite simple in design, it could give clear and interpretable rationale of each decision, which is particularly helpful in clinical practice, where transparency is important.

Deep Learning (DL) is a narrow field of machine learning that utilizes the artificial neural network applying several hidden layers, the model can explore and discover complex and non-linear interrelationships among the input variables and output variables (Samanta et al., 2023). These layered architectures have the capacity to release meaningful patterns and fine grained dependencies that would otherwise be missed in the conventional model building variants. Deep learning is an efficient architecture of the process which proceeds into several layers of non-linear processing and works with layers of effective representation, which often consists of tens or even hundreds of one-to-another layers. All of these layers are acquired automatically due to the exposure to training data (Kotsiopoulos et al., 2021).

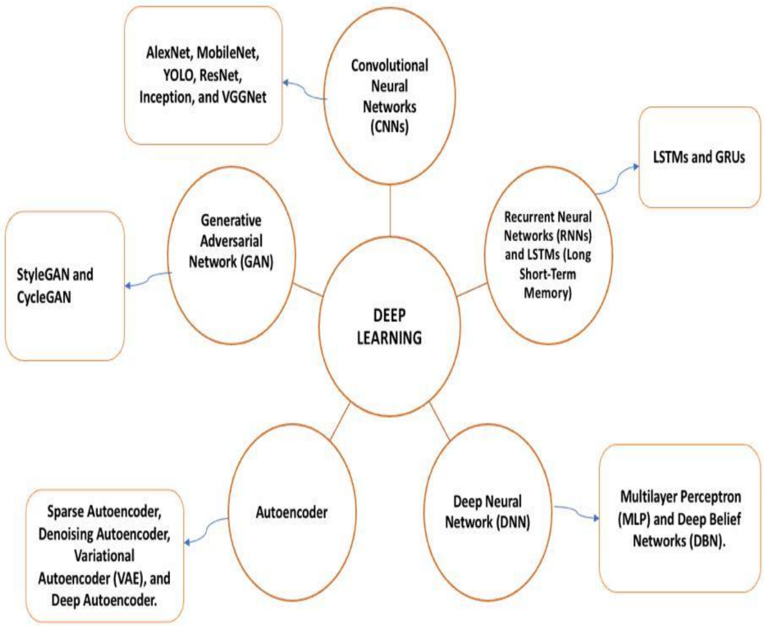

Figure 2.1 Deep Learning types and examples

As illustrated in Figure 2.1, DL algorithms can be categorised into five main types, namely:

a. Convolutional Neural Networks (CNNs) are primarily used for image recognition and spatial data analysis. A Convolutional Neural Network (CNN) is a specialized form of Artificial Neural Network (ANN) which is primarily developed for processing and analysing visual data, and this makes them highly effective in tasks such as image classification, pattern recognition, and object detection because they have the ability to automatically learn and extract important features from images (Samanta et al., 2023). Examples of CNN include AlexNet, MobileNet, YOLO, ResNet, Inception, and VGGNet. They are applied in precision farming for detecting crop diseases, identifying weeds, and analyzing soil conditions via drone images.

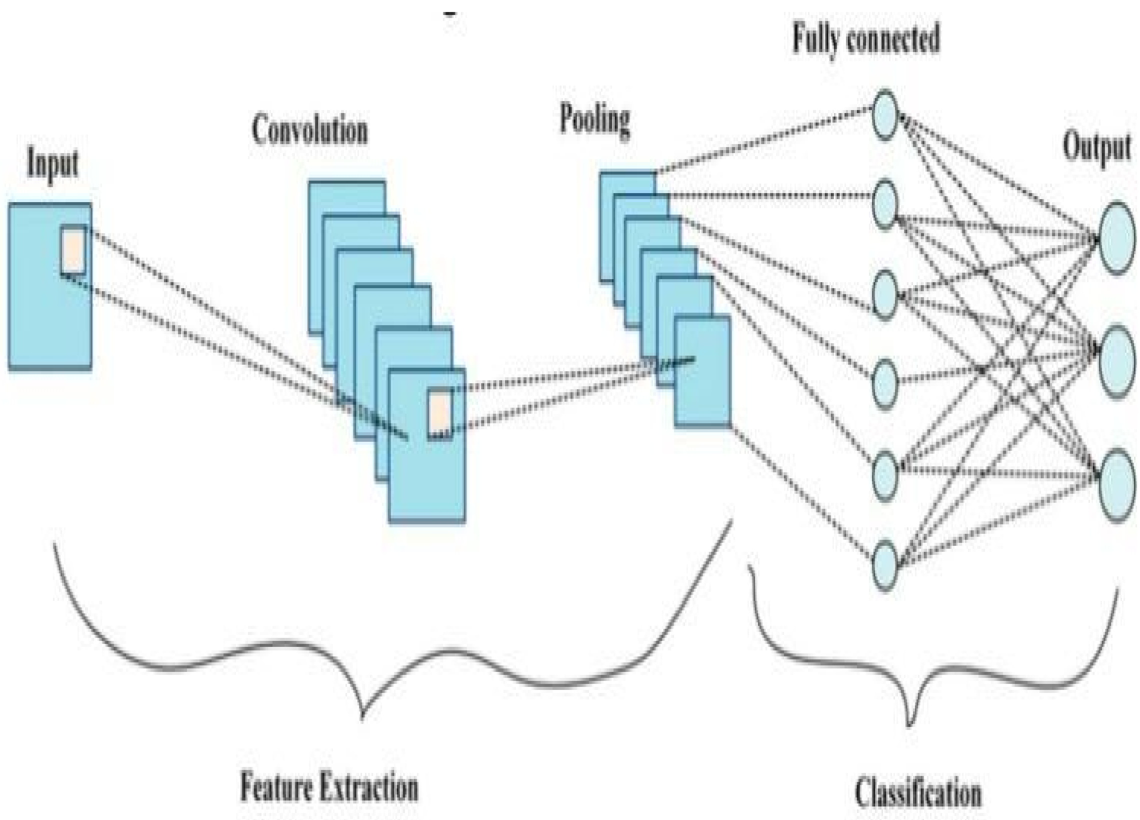

Figure 2.2: CNN architecture (Samanta et al., 2023)

Figure 2.2 illustrates that convolutional neural networks (CNNs) consist of several hierarchical layers containing interconnected processing units, where each node performs specific mathematical computations based on the outputs received from the preceding layer.

The convolutional layer is one of the most peculiar elements of Convolutional Neural Network (CNN) during which a small matrix called a kernel is systematically dragged across certain parts of your input data. The resulting process brings out a chain of feature maps that bring into consideration important spatial choices and textural features (Cong and Zhou, 2023). These filters are taken or trained under careful consideration to take out important attributes buried in the data. The features obtained as a result are fed to further layers and more refinement is done and finally helps in tasks like pattern recognition and object identification.

It has been experimentally proved that CNNs are especially responsive to supervised learning, where models can optimize their internal parameter values. Such flexibility enables CNNs to reliably work towards a wide variety of image analysis and image classification tasks and, as such, is extremely useful in fields such as medical imaging, surveillance and autonomous systems.

b. LSTM (Long/Short Term Memory) and Recurrent Neural Network (RNN): Recurrent Neural Network (RNN) is a custom kind of deep learning structure, made to read, and process data that arrives in sequence or time-ordered fashion. Such networks have internal feedback loops, and, hence, they can maintain contextual information over several steps in a series. It is this characteristic that renders them especially appropriate when performing tasks that contain temporal dependencies, i.e. speech interpretation and natural language modeling. RNNs perform extremely well in cases where past states have any impact on making future predictions due to the fact that the mechanism is able to memorize what has been given as input. Among the well-known examples of RNN-based networks are Long Short-Term Memory networks (LSTMs) and Gated Recurrent Units (GRUs) which were designed to address such limitations as the vanishing gradient problem of traditional or so-called vanilla RNNs. All these advanced forms promote more stability of the learning situation and, to a measure, allow a better prediction of the outcome of any complex sequential task. In precision farming, the RNN algorithms are used in predicting the weather, crop yield forecasting, and monitoring the growth of the plant in time.

c. Generative Adversarial Network (GAN): A Generative Adversarial Network (GAN), or adversarially-made network, is a type of neural net made up of two components: a generator, which generates synthetic data samples like pictures and videos, and a discriminator, which determines if the generated data is real or not. As both components work together under the same conditions and rules (i.e., both are trained at the same time), the generator continues to get better at creating fake data and the discriminator continues to get better at determining whether it is real. GANs are tasked with generating new data that mimics the training data. Examples of GANs are StyleGAN and CycleGAN. It is applied in agriculture for creating synthetic crop images for training models and simulating future field scenarios.

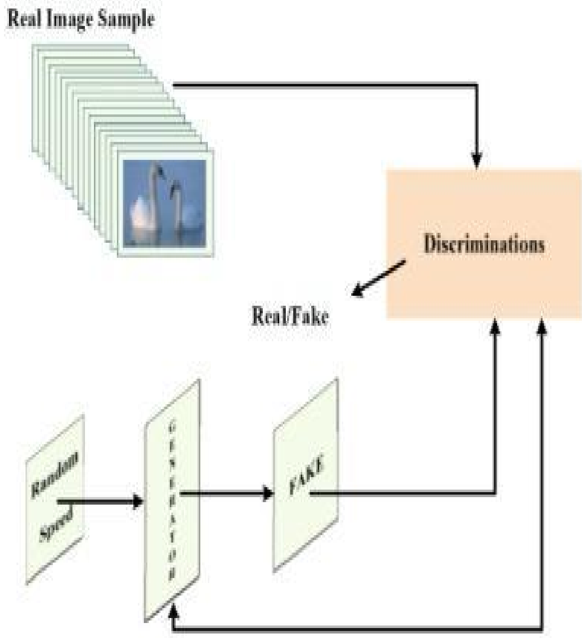

Figure 2.3: Architecture of a GAN (Samanta et al., 2023)

Figure 2.3 is an illustration of the GAN algorithm, which consists of two main components: the generator and the discriminator. The generator strives to craft artificial data that closely mimics the authentic dataset, attempting to deceive the discriminator into perceiving it as genuine. The discriminator, in its turn, is assigned with the issue of analyzing every single input it is exposed to in an attempt to define as to whether it is a product of the realistic distribution or a synthetically generated one. The interplays nurture the toughest competition in the face of which both models keep improving their functionalities.

D. A Deep Neural Network (DNN) is the model of artificial neural network which consists of a number of layers of widely networked processing elements (i.e. so-called artificial neurons) (Miikkulainen et al., 2019). Such an architecture is especially applicable to work with complex agricultural data so that it would be possible to use it to classify crops, detect plant diseases early, and predict the size of harvest. Through exploitation of the patterns on vast amounts of data, DNNs facilitate more accurate and evidence-based agricultural decision-making. Typical representations in deep learning of models under this category are Multilayer Perceptron (MLP), Deep Belief Networks (DBN), and Stacked Autoencoders, with each model holding its strengths with regard to its deployment in various predictive tasks.

2.3. Breast Imaging for Screening and Diagnosing

The medical imaging technique is one of the best techniques for diagnosing and evaluating cancer progression at its initial stages. It has three most common imaging techniques in the diagnosis of breast cancer as well, and they are mammograms, MRIs, and ultrasounds. One of the key requirements for efficient use of machine learning in breast PET. Also, in order to come up with reliable and precise machine learning models. Mammograms stand to be the most efficient way to identify breast cancer early among these. However, several aspects of mammography imaging are insufficient to identify the presence of malignancy. Breast cancer frequently manifests as a lump, whether it is calcified or not. However, the radiologist can assess the possibility of cancer by looking at the mass's location, size, form, density, and margins. Moreover, the components of the suggested system include picture preprocessing, image of breast segmentation, extraction of features, selection of features, and classification of features. X-rays can be used for breast image analysis.

A. Digital Mammograms:

X-ray is a mammography technique that is frequently utilized in clinical practice for screening and diagnostics (Kanaga et al., 2008). Mammography, therefore, is very suggestive of an early cancer since it shows high microcalcifications and has high sensitivity on fatty breast tissue. At the initial stage, clusters of microcalcifications are typically seen on mammograms as indicators of breast cancer. The early discovery of these microscopic calcium deposits is crucial for the effective course of treatment, as they can be seen well before any perceptible lesion has formed. Radiologists, on the other hand, typically make use of their shape, size, number, and distribution to make diagnoses. However, Malignant calcifications can vary in size, form, and density, and are usually very numerous, clustered, tiny, elongated, or dot-like. In general, benign calcifications have a more uniform shape, are more widely dispersed, bigger, more rounded, and fewer in number. Even for a seasoned radiology professional, distinguishing between benign and malignant lesions can be extremely difficult due to the tiny size of microcirculations. The microcirculations may now develop alone or in conjunction with masses or other regions of dense breast tissue.

Moreover, at this stage, Radiologists search for breast cancer indicators in women who do not exhibit symptoms of the disease by using screening mammography, which typically consists of two mammograms of each breast. A diagnostic mammography, which consists of fine-grained X-ray images of the worrisome area, is ordered if an anomaly is discovered.

B. Magnetic Resonance Imaging (MRI):

Magnetic resonance imaging (MRI) is a technique for detecting cancer cells at the initial stage, along with mammography and ultrasound. Here in MRI, magnetic fields are used to create extremely accurate transverse images that are three-dimensional (3D). But to obtain accurate 3D breast images from a human body MRI, a significant radiation dose is necessary. However, as a result, the affected region changes quite noticeably when we utilize an MRI, and no cancer that cannot be spotted with any other approach is discovered. Breast MRI is crucial for detecting problems in people who are highly susceptible to breast cancer.

- Elevated chance of breast cancer development.
- An assessment of the staging time.
- Follow-up neoadjuvant chemotherapy (NAC).

Assessing a secondary lymph node region in cases when mammography was unable to pinpoint the original site. When done according to benchmark standards and best practices, a breast MRI takes thirty to forty minutes.

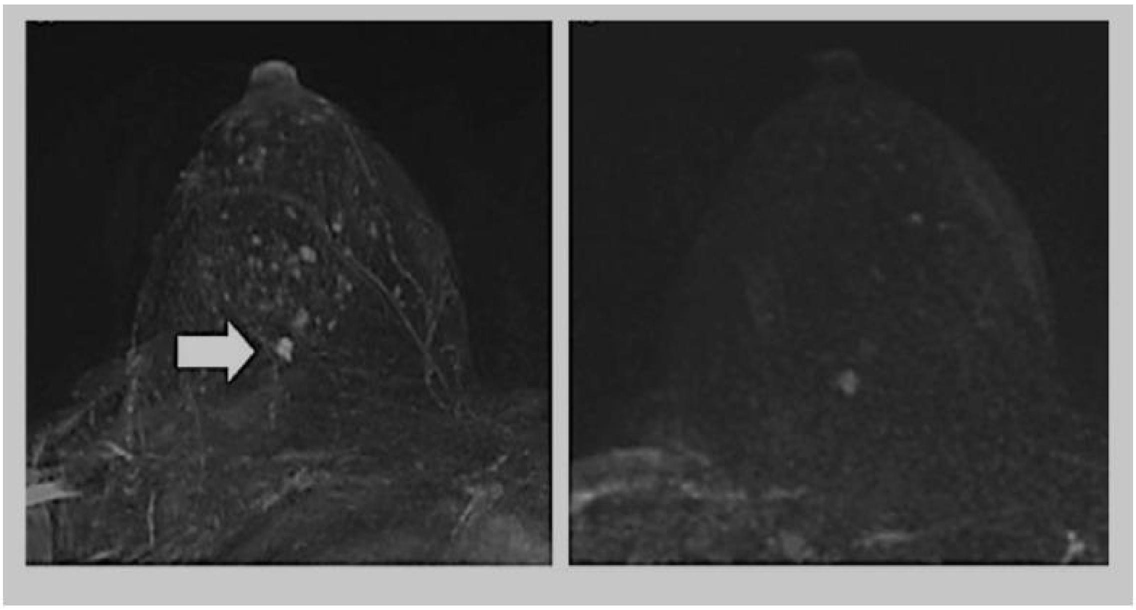

Figure 2.4 An MRI image

D. Thermography Images:

Thermal imaging, also known as breast thermography under a microscope, is produced under a microscope. It allows one to investigate the relationship between the structural and functional characteristics of an organ, tissue, or cell and its microscopic anatomy. This non-invasive and painless approach is used to find breast alterations that may be signs of breast cancer. However, by being able to recognize the different body parts that indicate an unusual temperature shift, a camera that has an infrared thermal nature, which functions to transform light which are infrared light to impulses of electrical charges and therefore shows it as a thermogram, could be used to detect and predict cancer of breast cancer. This method of diagnosis is called thermography. Also, it is important to note that Artificial Intelligence (AI) and thermal imaging work well together to detect breast cancer at its early stage, and the latter is expected to have a prediction that is very good in accurate.

E. Positron Emission Tomography (PET):

Positron Emission Tomography or breast PET, is an imaging technique that is used in the field of medicine to show and characterize activities that are metabolic activities in the tissue of the breast. Using this method, a small quantity of a radioactive tracer, which is typically a substance that is based on sugar, is injected into the patient's circulation. On this note, positron particles, which are positively charged particles, are released when the tracer builds up in areas with increased metabolic activity, such as malignant cells. However, the PET scanner detects the gamma rays that are produced when these positrons interact with the tissue's electrons to create pictures. It is important to note that breast PET imaging relies heavily on machine learning and particularly on boosting picture quality to increase the precision of cancer detection, and also supporting diagnosis. Moreover, nuclear medicine modalities like PET or scintigraphy are less useful in assessing early-stage breast cancer when compared to other imaging techniques. Furthermore, there are not as many publicly accessible breast PET datasets as there are for other medical imaging modalities. Therefore, it is crucial to stress that having access to high-quality, well-annotated datasets is for breast PET imaging analysis, access to such datasets is essential.

2.3 Review of Related Works

More recently, Adeniji, Bello, and Yusuf (2025) developed a CNN-BiLSTM architecture for breast cancer histopathological image classification. Their model achieved high classification accuracy and demonstrated the effectiveness of deep learning techniques in cancer diagnosis. However, the study was limited by dataset size and focused exclusively on image classification without integrating hereditary, lifestyle, and clinical risk factors.

Shravya et al. (2019) all contributed positively to their work of research where they performed a comparative study of machine learning models, which included the K-Nearest Neighbor, the Logistic Regression and the Support Vector Machine (SVM), for the main purpose of classifying tumors in other to know if it is benign or malignant. They, however, trained a model on a dataset from the UCI repository, and at the end of the process, the model was evaluated based on sensitivity, accuracy, specificity, precision, and lastly, false positive Rate. They implemented the model using Python and executed it using Spyder in a Python development environment, which was scientific. However, their experiments indicated that the SVM algorithm achieved the highest level of accuracy at the level of 92.7%, thereby making it the algorithm that is most effective and suitable algorithm for predictive analysis.

Rufai, Musa, and Abdullahi (2021) developed a breast cancer prediction model using Support Vector Machine and Logistic Regression algorithms. Their findings showed that machine learning models could achieve satisfactory prediction accuracy when trained on clinical datasets. Despite these promising results, the study relied solely on structured clinical data and did not incorporate medical image analysis.

Bhise et al (2021) all contributed to this research to identify breast cancer as a leading cause of death incidents that are related to cancer. Their work highlighted the importance of detecting cancer early. They made use of different techniques of machine learning as they explored diagnosing cancer of breast cancer. At the end of their research, they developed a machine learning model that makes use of the Convolutional Neural Network (CNN) for classification and the Recursive Feature Elimination (RFE) to select the important features.

They, however, compared the performance of five other different algorithms, which include: the Random Forest algorithm, the Support Vector Machine (SVM), the K-Nearest Neighbors (KNN), the Naïve Bayes, and the Logistic Regression algorithms. Moreover, they conducted their experiment using the BreaKHis 400X dataset and at the end of everything, they evaluated the accuracy and precision of the model that they developed with the use of ReLu activation function so that they may predict the results in the form of probabilities.

Tahmooresi et al. (2018) engaged in a broad study aimed towards increasing the accuracy of diagnostic procedures. They have presented in their study a composite model combining various machine learning techniques. They combined a number of algorithms that consisted of the Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Decision Tree (DT). The researchers tried to combine these various approaches to enhance the efficacy of the model in diagnosing breast cancer. The hybrid framework has been built to serve a high range of data inputs thereby enhancing its dynamism and strength in the various diagnosis settings. The model would take into consideration different types of inputs such as blood test results and medical imaging and thus would have a broad and flexible approach, in detecting breast cancer.

By launching a joint study aimed at the enhancement of both the diagnosis and prognosis of breast cancer through the application of machine learning (ML) methods, Sharma et al. (2018) have contributed to the most significant issue. In their quest, they considered a diagnostic method that has been introduced with the help of Python with the help of which they made an ML block. They sought to illustrate how algorithmic analysis can be used to aid early diagnosis and there may be an opportunity to make clinicians make better decisions based on this.

Allugunti (2022) devoted a close study to the task of breast cancer prognosis, offering a Computer-Aided Diagnosis (CAD) framework developing an algorithm structure that is supposed to divide the patients into three classes: malignant, benign (non-cancerous), and healthy (absence of any signs of cancer). The system suggested used three well known algorithms of classifications. The models of Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Random Forest (RF) make a special role in the model performance. Moreover, it investigated how the image pre-processing tactics affected mammographic data and how the sharpness of the medical examinations could be raising substantially the level of accuracy and accuracy of the findings.

Vyas et al. (2022) have carried out a very sound research study with a goal to improve the diagnostic accuracy of breast cancer detection. In their publication, they came up with a model that combined several machine learning models such as Artificial Neural Networks (ANN), Decision Trees (DT), K-Nearest Neighbors (KNN), and the Support Vector Machines (SVM). By reconciling these various methods, the researchers aimed at reinforcing the accuracy as well as efficiency of the breast cancer classification thereby developing more dependable and early diagnosis.

In their endeavor to make the three classifiers more accurate and efficient (Naive Bayes (NB), Sequential), Basker et al. (2021) toiled with their team to conduct research. SMO (Minimal Optimization) and classification into the Decision Tree (J48). By the close of their research evaluation, they have tried the model that they have developed with two databases, namely, the dataset of Wisconsin Breast Cancer (WBC) and another dataset of the cancer of the breast. Each of the classifiers was however tested on 10 fold cross-validation against measures of precision, ROC curve, accuracy, recall and standard deviation. Moreover, at the end of their research, the results showed that applying a resample filter improves classifier accuracy, especially the SMO, to be specific, performs highest on the WBC dataset, while the J48 outperforms the others on the dataset for the cancer of the breast.

Nallamala et al (2019) all contributed to the positive process of embarking on a tremendous journey of research. Their research focused mainly on using artificial intelligence (AI) to detect breast cancer. Specifically, the study introduced an ensemble voting scheme that was adaptive and was tested on the dataset of the Wisconsin Breast Cancer (WBC). Their goal in embarking on the research was to demonstrate and compare how the Convolutional Neural Networks (CNN) and the logistic algorithms can effectively detect the cancer of the breast, even with variables that are reduced variables. Most importantly, the study was aimed at distinguishing between the two types of tumours, which are benign (non-cancerous and malignant (cancerous).

Omondiagbe et al. (2019) looked into how well different machine learning methods work for diagnosing breast cancer. They focused on machine learning methods that utilise the WDBC dataset. Specifically, they evaluated the machine learning techniques of SVM-RBF, Naïve Bayes, and ANN. To improve classification accuracy, they created hybrid classifiers by combining these techniques with feature extraction and feature selection techniques. The study's purpose was to evaluate the effectiveness of these techniques in terms of predicting breast cancer with WDBC data; thus, these techniques were combined with LDA-dimension-reduced data and all classifiers were trained and tested using the transformed dataset before it was fed into the SVM model. The results of their study were remarkable. Among other things, their method achieved accuracy of 98.82%, specificity of 99.07%, sensitivity of 98.41%, and Area Under the ROC Curve (AUC) of 0.9994. These results support the ability to use machine learning classifiers that integrate dimensionality reduction methods to assist with breast cancer diagnosis.

Oyediran, Adekunle, and Ibrahim (2022) proposed a machine-learning-based breast cancer prediction system using clinical datasets collected in Nigeria. The study demonstrated that machine learning algorithms could effectively predict breast cancer risk among Nigerian women. However, the system lacked image-processing capabilities and did not provide personalized preventive recommendations.

Table 2.4 Summary of Literature Review

The table below summarises the relevant literature most related to MammoCareAI and its limitations. These analyses motivated the design of MammoCareAI by identifying strengths, weaknesses and gaps in the existing.

Author(s)	Technique Used	Contribution	Shortfall

Adeniji et al. (2025, Nigeria)	2D CNN + BiLSTM	Used deep learning for breast cancer detection on histopathological images.	Small dataset; imaging-only approach; no comprehensive risk prediction.
Bhise et al. (2021)	Machine Learning and Comparative Approach	Highlighted the importance of early breast cancer detection.	Developed using an outdated dataset, reducing effectiveness.
Tahmooresi et al. (2018)	Hybrid Machine Learning	Improved breast cancer detection performance using multiple machine learning algorithms.	System lacked specificity and was unable to detect cancer with high precision.
Rufai et al. (2021)	Support Vector Machine (SVM) and Logistic Regression	Utilised SVM and Logistic Regression for breast cancer prediction.	No real-time web platform for deployment.
Sharma et al. (2018)	Systematic Literature Review	Applied ML to contribute to improving breast cancer diagnosis and prognosis.	Developed mainly with Python and lacked a specific classification algorithm.
Allugunti, V. R. (2022)	Computer-Aided Diagnosis (CAD)	Classified patients into cancer, non-cancer, and non-cancerous	Only grouped patients into

	and Machine Learning	categories.	categories without explicitly determining cancer status.
Vyas et al. (2022)	Hybrid Machine Learning	Their study improved the diagnosis of breast cancer by enhancing its accuracy.	Did not implement a specific machine learning algorithm.
Basker et al. (2021)	Machine Learning	Improved the accuracy and efficiency of Naïve Bayes (NB), Sequential Minimal Optimisation (SMO), and Decision Tree (J48) classifiers.	The dataset used for training was not sourced from a reputable repository.
Nallamala et al. (2019)	Literature Review	Distinguished between benign (non-cancerous) and malignant (cancerous) tumours.	Relied solely on text-based data, which could lead to inaccurate results.
Omondiagbe et al. (2019)	SVM, ANN, and Naïve Bayes	Reduced feature dimensionality using Linear Discriminant Analysis (LDA) before applying classification algorithms.	Focused mainly on comparative analysis of machine learning algorithms.
Shravya et al. (2019)	K-NN, Logistic Regression, and SVM	Conducted comparative analysis to distinguish between benign and malignant tumours.	Designed primarily for comparison and could not directly determine cancer presence.

Oyediran et al. (2023)	SVM, Logistic Regression, and K-NN	Applied classical machine learning algorithms in order to predict the occurrence breast cancer.	Ignored lifestyle and genetic risk factors and lacked web-based deployment.

2.5 Research Gap

According to the literature review, together with advancements being made in using statistical models, machine learning and, more recently, deep learning methods for detecting and predicting risk of breast cancer. Studies conducted worldwide have found that high accuracy can be attained by using Convolutional Neural Networks (CNN) when analysing medical images; however, there are still many unanswered questions around how to use machine learning to predict cancer in scarce research environments such as Nigeria and Africa in general. Most breast cancer risk prediction models developed for Nigerian women to date have relied on traditional statistical or epidemiological approaches. As such, they are not able to capture complex, non-linear interactions among family history, clinical and lifestyle risk factors, while the algorithms that achieved reasonable classification accuracy were mostly experimental, but not deployed as a user-facing web-based platform for real-time application. To address these gaps, we have created a web-based automated breast cancer detection and risk prediction system, MammoCareAI, for Nigerian and African women.

CHAPTER THREE

SYSTEM ANALYSIS AND DESIGN

3.0 Introduction

This chapter presents the analysis and design of an intelligent web-based Artificial Intelligence (AI) system, MammoCareAI, for risk prediction and early detection of breast cancer by women in Nigeria and across Africa. MammoCareAI, which is developed in response to gaps identified in existing literature, supports preventive awareness and personalised risk assessment by women.

MammoCareAI employs Convolution Neural Networks (CNNs) to provide a personalised breast cancer risk score and prevention recommendations based on hereditary, clinical and self-reported lifestyle information. We use a combination of Prototype–V Model for our entire development process, where the phases are defined in the Product Requirement Document (PRD) and Software Requirement Specification (SRS), and every phase of development is validated, with continuous, iterative user evaluation and testing.

3.2 System Analysis

3.2.1 Analysis of the Existing System

Traditional machine learning algorithms:

Traditional machine learning algorithms such as SVM, KNN, RF, and DT are used for breast cancer classification. These models often depend on manually engineered features extracted from diagnostic imaging data, such as tumour shape, texture patterns, and dimensional attributes. They can work efficiently in case the data can be organised well and feature description can be understood in particular and uniform. Their accomplishments have some outstanding attributes as listed below:

i. It is quite effective for smaller datasets.

ii. It is relatively easy to interpret and understand.

iii. It is highly accurate.

Nevertheless, despite their recognized advantages, these models exhibited several limitations due to their strong dependence on features that were manually extracted. Such dependency usually limits their flexibility, particularly when used over a more varied or less rigid set of data, where manually designed features may not be able to reflect the subtle or complicated tendency within the data.

Deep Learning Models:

Convolutional Neural Networks (CNN) Deep learning solutions have progressively become a trend in medical image interpretation, and breast cancer detection is one of the applications. In contrast to early models, CNNs have the capability of learning meaningful features themselves which are derived exclusively from imaging data rather than manually-crafted features and substantially reduce the need of deep handcrafting. One of their greatest strengths consists in the following:

a. CNNs can effectively learn complex and abstract patterns with raw images based on intuitive study and this can help them to deliver better results, particularly when dealing with giant and heterogeneous datasets.

b. CNNs perform better than the traditional methods in terms of accuracy and robustness especially in tasks concerning complicated visual data. They can generalize well on various imaging scenarios thus making them very effective on diagnostic works. However, despite these outstanding qualities, these models do not bear any disadvantages. The major weakness is that they require the large amount of well-labeled information. Lack of adequate enough annotated examples could lead to overfitting in the network thus decreasing its generalisation and trustworthiness in practice.

3.2.2 Weakness of the Existing System

1. Computational complexity and resource consumption: Hybrid machine learning frameworks, particularly those that incorporate deep learning like operations into more traditional types of algorithms regularly face severe computation requirements. These resource-demanding systems involve a lot of processing power required both in the course of learning and real-time test. This pressure can be caused by the need to work huge data and at the same time running several models, which can either run concurrently or be sequential in order to give results.

2. Low interpretability and transparency: One of the central challenges one must face regarding hybrid machine learning architectures is as follows: a lack of transparency and low levels of interpretability. Such systems commonly combine various sophisticated algorithms; e.g. combining neural networks with decision trees or using sophisticated forms of ensemble methods, which in combination produce very deep and highly intertwined decision branches. As a result, it provokes an extremely hard trace of the reason behind a certain production. It is quite unsettling in the medical sector considering practitioners and patients can only trust a diagnosis after receiving clear, evidence-based explanations. In a situation whereby the inner logics of a system is not exposed there are chances that the clinicians might not view, test or even justify the conclusions of the model. This confusion may weaken the trust in the

application of such tools in sensitive tasks, such as detection of cancer, placing doubt in the implementation into healthcare system.

3. Data Imbalance and predictive bias:

Another and rather frequent issue in the breast cancer detection datasets is the observable class imbalance. In such medical datasets, a significantly higher number of benign cases are usually prevalent as compared to the malignant ones. Such unequal representation may lead in internalizing of the data by hybrid models, a biased perception of the data, most often on the side of the dominant class. Even in situations where the model reports high overall performance metrics, its effectiveness may be compromised by a failure to detect minority class instances with sufficient reliability.

3.2.3 Analysis of the Proposed System

The system proposed for breast cancer offers a layered approach aimed at overcoming several shortcomings found in traditional diagnostic techniques. Through the deliberate integration of diverse machine learning strategies, this hybrid architecture seeks to improve forecasting accuracy, reduce computational strain, and generate results that are easier for healthcare professionals to interpret. For the model's training process, data will be drawn from Kaggle, a reputable and well-established platform recognised for hosting a broad range of high-quality, reliable medical datasets.

The system will be designed with a dual-structure architecture, comprising two integral segments. The first is a user-oriented interface, crafted to ensure smooth interaction and usability. The second is the analytical core, the machine learning model itself, which will function as the engine behind all diagnostic predictions. Together, these components will work in tandem to create a reliable, efficient, and interpretable solution tailored for medical use. The model of the system, however, would be developed using convolutional neural network. It would be trained to accept images as input data. However, by implementing the system that has been proposed above, the system will offer several advantages to patients, health workers, and policymakers.

3.2.4 Advantages of the Proposed System

The proposed system is necessary because:

i. Breast cancer deaths are increasing in Africa
ii. Early detection services remain inaccessible
iii. AI can reduce dependence on scarce specialists
iv. Users need affordable digital alternatives
v. Preventive healthcare remains underdeveloped in Nigeria

MammoCareAI addresses these realities.

3.2.5 System Requirements

System requirements are the conditions, capabilities and standards that a system must meet to obtain the desired objectives. They are used throughout the development of a system, to define the system's behaviours and performance. These requirements should be clearly identified to guarantee that the solution developed will satisfy the user's needs and will be functioning as intended.

In general, there are two types of system requirements: functional and non-functional. The non-functional requirements are concerned with the quality attributes, whereas the functional requirements are concerned with the services and operations provided by the system. Combined these requirements serve as a basis for designing, implementing and evaluation of the proposed Breast Cancer Detection and Risk Prediction System.

A. Functional Requirements

1. Data Acquisition and Preparation

The system should be able to collect relevant breast cancer data from multiple sources such as medical images, patient demographic data, and clinical records. It should also clean and standardise the data it collects, addressing missing data, inconsistency, noise and format, to ensure that it is of high quality and useful for the organisation.

2. Feature Extraction and Selection

The system should be able to recognise patterns and characteristics that relate to breast cancer from the available data to be meaningful. It should also be able to implement feature selection methods that would decrease the complexity of the data while retaining the most relevant features that could be used to correctly predict the outcome.

3. Prediction models development.

The system should be able to design and train predictive models for detection of breast cancer. It should enable the use of machine learning and deep learning methods such as Convolutional Neural Networks (CNNs) and allow fine-tuning model parameters for best performance. Moreover, the system should test trained models with appropriate performance measures to check the effectiveness of the models.

4. Prediction and Decision Support

The system should be able to calculate risk estimates for breast cancer, in real time, from inputs received from the user. It should communicate prediction results in a clear and comprehensible way to support decision making by health care practitioners. The appropriate graphs and diagnostic information should also be provided to aid in interpretation of results.

B. Non-Functional Requirements

1. Performance

Data processing efficiency and the prediction results should also be provided within reasonable time frame. The critical nature of the healthcare domain requires swift execution for prompt diagnosis and decision-making.

2. Scalability

The system should be expandable to handle more users and larger data sets without noticeable degradation in speed, accuracy or overall performance.

3. Reliability

System should run in a uniform manner with minimum interruptions and failures. High availability is required to provide the ability for healthcare professionals to call prediction services as needed.

4. Accuracy

The system should give highly accurate prediction results, correctly identify the cases of breast cancer and reduce the number of false-positive and false-negative results. It is essential to have high predictive accuracy to enhance diagnostic confidence and to guide successful patient management.

3.3 System Development Methodology

This study makes use of two complementary methodologies: Deep Learning Experimental Methodology and Object-Oriented Analysis and Design (OOAD), which helps in the development of a comprehensive Breast Cancer Risk Prediction System. The Deep Learning Experimental Methodology sets up the process for development, training, validation and evaluation of the Convolutional Neural Network (CNN) model that is used for breast cancer risk prediction. The OOAD approach, on the other hand, is utilized in the design and implementation of the software system, which enables users to access and interact with the prediction system.

A detailed analysis of the problem domain, system requirements, is the beginning of the development process. This stage requires us to identify both the functional and non-functional requirements of our proposed system, assessing the needs and expectations of users, and establish the overall system architecture. It serves as the foundation for ensuring that the developed system effectively meets its intended objectives while maintaining the desired level of performance, reliability, and usability. This analysis aids in making sure that the solution created fits the requirements of the users and that it can address the problems involved in breast cancer risk assessment and prediction. The Deep Learning Experimental Methodology is a systematic progression of activities to design a predictive model: data collection, data preprocessing, partitioning of dataset, design of model, training of model, validation of model, testing of model and evaluation of model performance. The dataset of breast cancer is preprocessed through a set of pre-processing steps, including data cleaning, normalizing data, augmenting data if needed, and extracting features from the data. After proper preparation of the data, the CNN model is created and trained to detect intricate patterns and relationships between variables associated with breast cancer risk. The predictive capability of the developed model was assessed through a comprehensive set of performance indicators. These measures were used to evaluate the model's ability to correctly classify cases, identify positive and negative outcomes, maintain balanced predictive performance, and distinguish between risk categories with a high degree of reliability.

At the same time, the OOAD methodology guides the software engineering aspect of the study. This makes them smaller, more distinct subsystems, which makes it easier to make future changes, more flexible, maintainable and scalable. In the analysis phase, the system actors, use cases, classes, and relationships between these are identified and modeled, which helps to clarify the functions of the system. In order to see both the structural and behavioral view of the application, Unified Modeling Language (UML) diagrams are used. They are Use case diagrams, class diagrams, sequence diagrams and activity diagrams which are useful in the effective design and implementation of the proposed system.

After the design phase, the application modules, integration with the database, user interface, and communication between the software platform and the CNN prediction model are implemented using the principles of OOP. The outcomes from this system offer an intuitive user interface where users can enter relevant breast cancer risk data and receive predictive results from the trained CNN model.

The availability of the Deep Learning Experimental Methodology combined with OOAD is well suited to the study, as this approach helps not only scientific development of the accurate prediction model, but also engineering of the software system to be robust and user-friendly. This comprehensive approach will ensure the eventual Breast Cancer Risk Prediction System is accurate, efficient, scalable and can support early risk assessment and informed healthcare decision-making. Figure 3.1 will present the Proposed Methodology Framework of the new system.

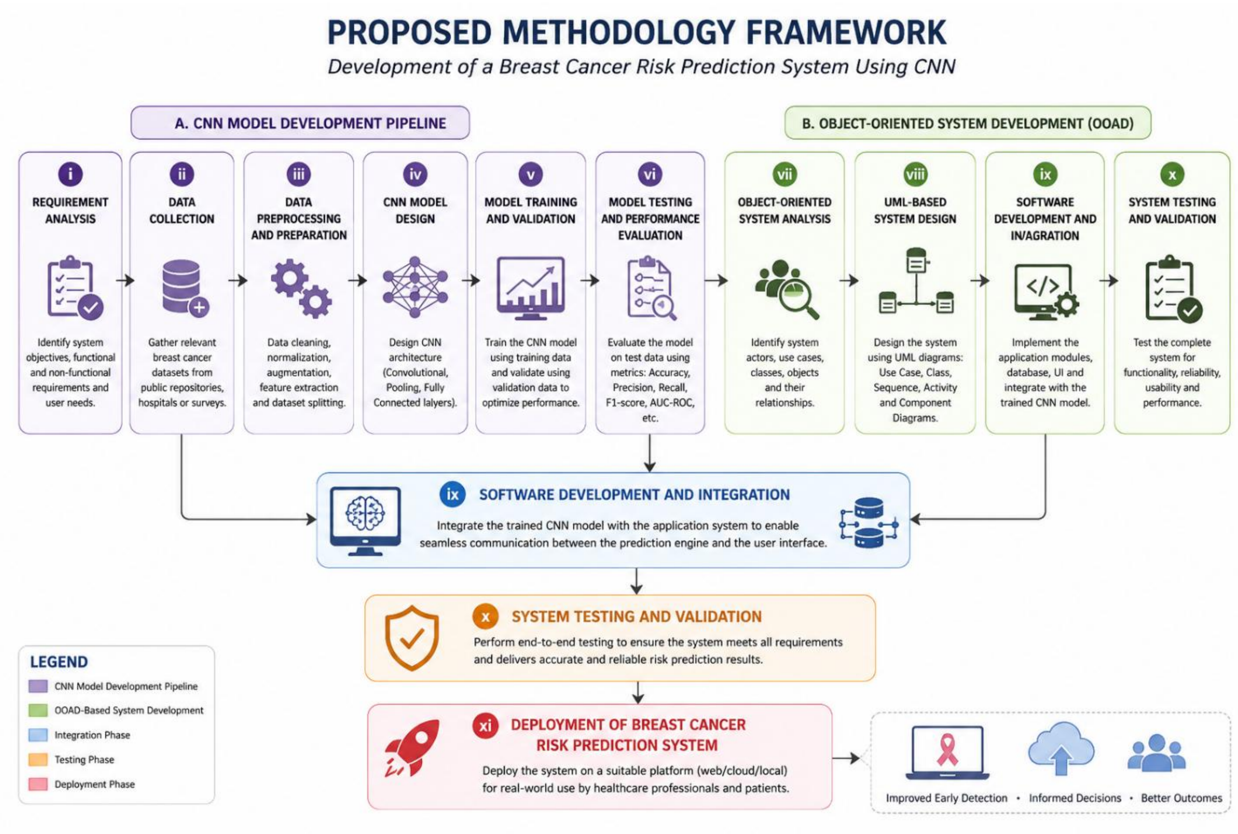

Figure 3.1: Proposed Methodology Framework

Figure 3.1 presents the diagram illustrating the proposed system methodology framework in which a hybrid Methodology Employed to develop a breast cancer risk prediction system through Convolution Neural Networks and Object-oriented Analysis & Design (OOAD), showing the sequence of steps from requirements analysis, data preparation, model development, implementation of software systems, testing of systems, and deployment. The requirement analysis was performed immediately after analysing the proposed system, where we outlined the functional and non-functional requirements.

3.3.1 Method of Data Collection

The proposed system collected breast cancer datasets from the Kaggle online repository and it was selected because it provides publicly accessible and well-structured datasets for machine learning research. The Kaggle breast cancer datasets contain records which are very relevant to breast cancer diagnosis and risk assessment and are available for download in machine-readable format, which is suitable for analysis and model development. The collected dataset included patient-related attributes used as input variables for prediction, which prompted us to review them in order to ensure completeness, relevance, and suitability for CNN-based prediction. At the end, only the data required for breast cancer risk prediction were retained, serving as the primary source for training, validation, and testing for our proposed model. The dataset we used in this study contains Benign and Malignant breast ultrasound images.

Table 3.1 Dataset Collection

Class	Number of Images
Benign	421
Malignant	421
Total Images	842

3.3.2 Data Preprocessing and Preparation

The collected dataset was inspected in order to identify missing values, duplicate records, and inconsistencies, which made us remove irrelevant attributes that do not contribute to breast cancer risk prediction. The missing data were handled using appropriate techniques such as replacement, interpolation, or deletion where necessary and duplicate records were eliminated in order to improve data quality and prevent bias which might arise during model training.

This was the time to perform data cleaning to make sure that data is accurate, consistent, and reliable; categorical variables were also converted to numerical values that could be used with machine learning algorithms; and feature scaling and normalisation were performed, to standardize data values. The data was properly balanced to ensure a good performance of the model and to deal with class imbalance. A three-part dataset was created, composed of the training, validation, and testing datasets. The training dataset was utilized to discover the patterns and characteristics needed to build the model, while the validation dataset was used to observe the training process and aid in tuning the parameters of the model. After completing these stages, the final model's performance was measured using the test dataset and its performance in predicting previously unseen instances was also measured. The study ensured the Input data were resized and reshaped into the desired dimensions of CNN model and feature matrices were converted into tensors suitable for deep learning processing. We applied batch generation techniques in order to improve training efficiency.

3.5.2 Unified Modelling Language (UML) Diagrams

Unified Modelling Language (UML) diagrams are a structured and standardized way of representing the design and functionality of a software system. They are commonly employed in software engineering to make complicated system structures easier to comprehend and communicate between software developers, software systems analysts, software designers, and other system stakeholders. UML diagrams help to make implementation more straightforward by providing visual representations of the interactions and operation of various parts of a system. The use case diagram is one of the most crucial UML tools used in this study. This diagram represents the relationship between the various users (and outside entities) of the proposed system and the services or functionality that they can use. The use case diagram visually represents these interactions to make the functional requirements of the system easier to understand and to give the reader an understanding of how the system is expected to function. The activity diagram is another key UML tool which emphasizes the behavioral part of the system. It shows the series of activities, actions, and decisions that happen while systems are running. The activity diagram shows the flow of activities from one activity to another, giving a complete picture of the operation of the system. This is helpful in determining workflow dependence, possible delays, decision flows, and opportunities to improve performance.

A. Use Case Diagram of Proposed System

The proposed system uses case diagram has four elements. The first is the actor(s) – the external user(s)/entities that are related to the system. The second one is the use cases which represent the different functions and services served by the system. The third one is the connection between actors and use cases, which depicts the interactions between users and the functionalities available. The last one is the system boundary, which sets the boundary of the proposed system and makes it easy to separate external entities that interact with the system from system internal functions. The use case diagram is used to create a system overview of the operational requirements and user interactions of the system, using the following components.

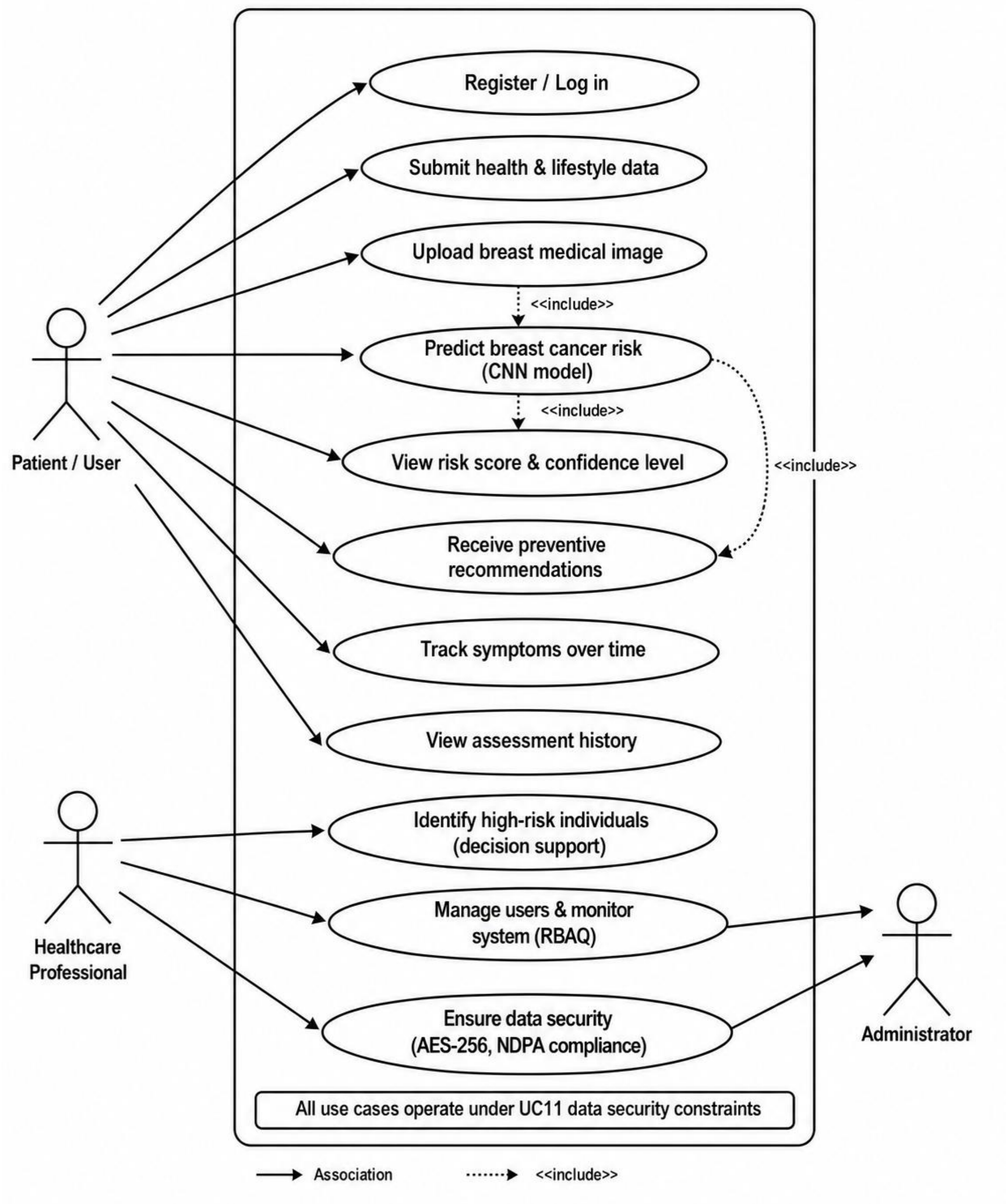

Figure 3.2: Use case diagram of the proposed system.

Figure 3.2 presents a use case diagram which visualizes the functional interactions between the Patient/User, Healthcare Professional, and Administrator in the Breast Cancer Detection & Risk Prediction System. Patients/users can register for the system, provide health and lifestyle information, upload breast medical images, obtain breast cancer risk prediction scores generated from the CNN machine learning (ML) model, receive preventative recommendations for managing their health, track their symptoms, and access their historical assessment data. Healthcare Professionals will use the system to identify individuals that are at high-risk and provide clinical decision-making support, whereas Administrators will be responsible for managing users, tracking system activity, and monitoring security controls. The use case diagram also outlines the various relationships among system functions - risk prediction represents the core workflow processes that deliver risk assessment and recommendation generation, executed within established data security and privacy compliance requirements.

B. Activity Diagram of the Proposed System

Activity diagrams could be referred to as the best tools that could be employed for visualizing the flow of activities or processes within a system. Figure 3.3 illustrates an activity diagram outlining the steps that are involved in implementing a breast cancer detection system using the techniques of machine learning:

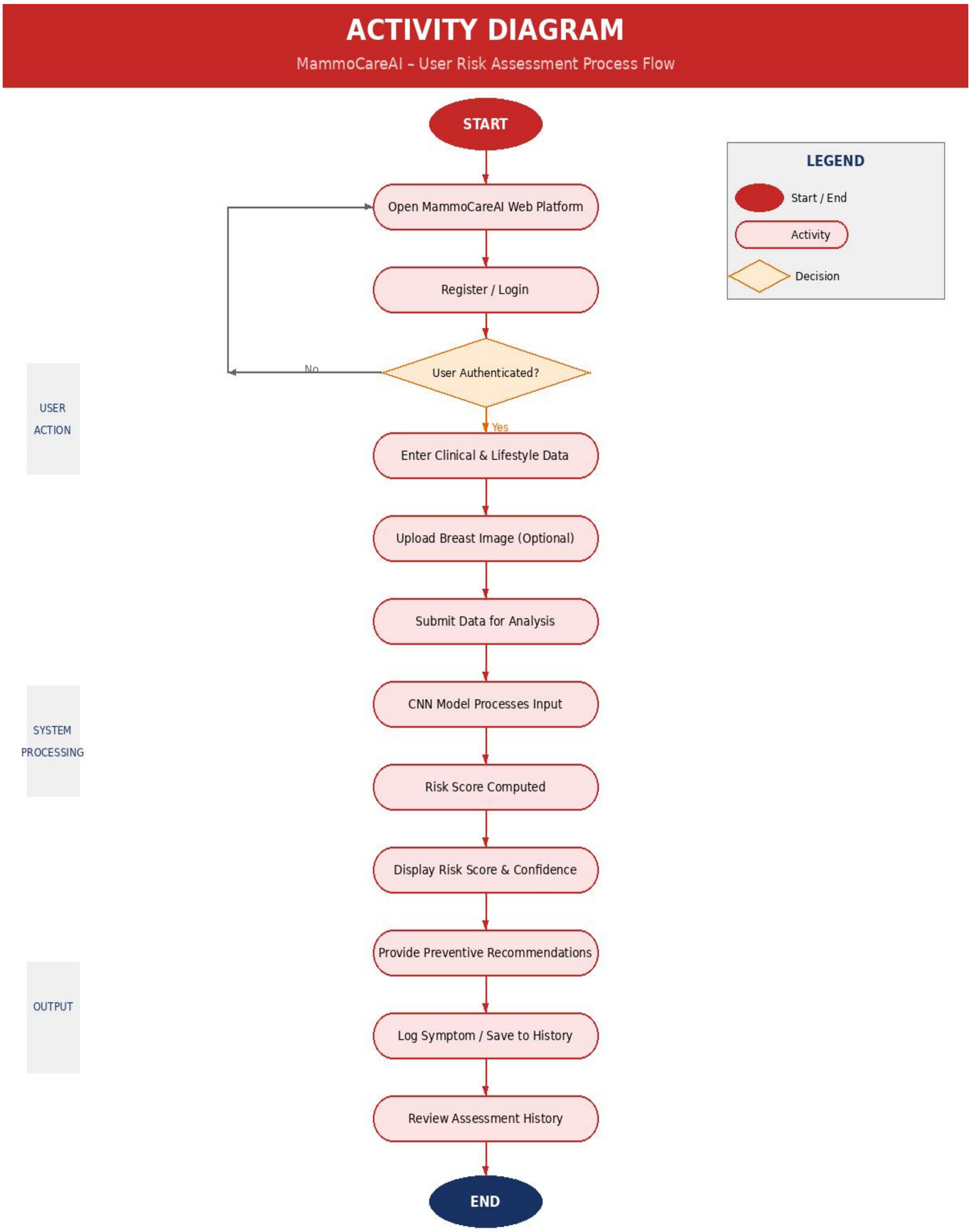

Figure 3.3: Activity diagram of the proposed system.

Figure 3.2 provided above is an activity diagram of the proposed system, and it provides a clear visualization of the sequential flow of activities that are involved in the implementation of a breast cancer detection system using hybrid machine learning techniques. It depicts all the individual processes that are involved in predicting the detection of breast cancer, which range from data collection and preprocessing to model development, evaluation, and deployment.

C. Class Diagram of the Proposed System

This section presents the proposed system class diagram, which is a UML framework or structural diagram used to represent the static architecture of a software application. It illustrates the various classes within the system, their attributes and methods, as well as the relationships and interactions that exist among them. By providing a clear representation of the system's structure, the class diagram serves as a guide for software design and implementation. Figure 3.3 shows the class diagram developed for the proposed system.

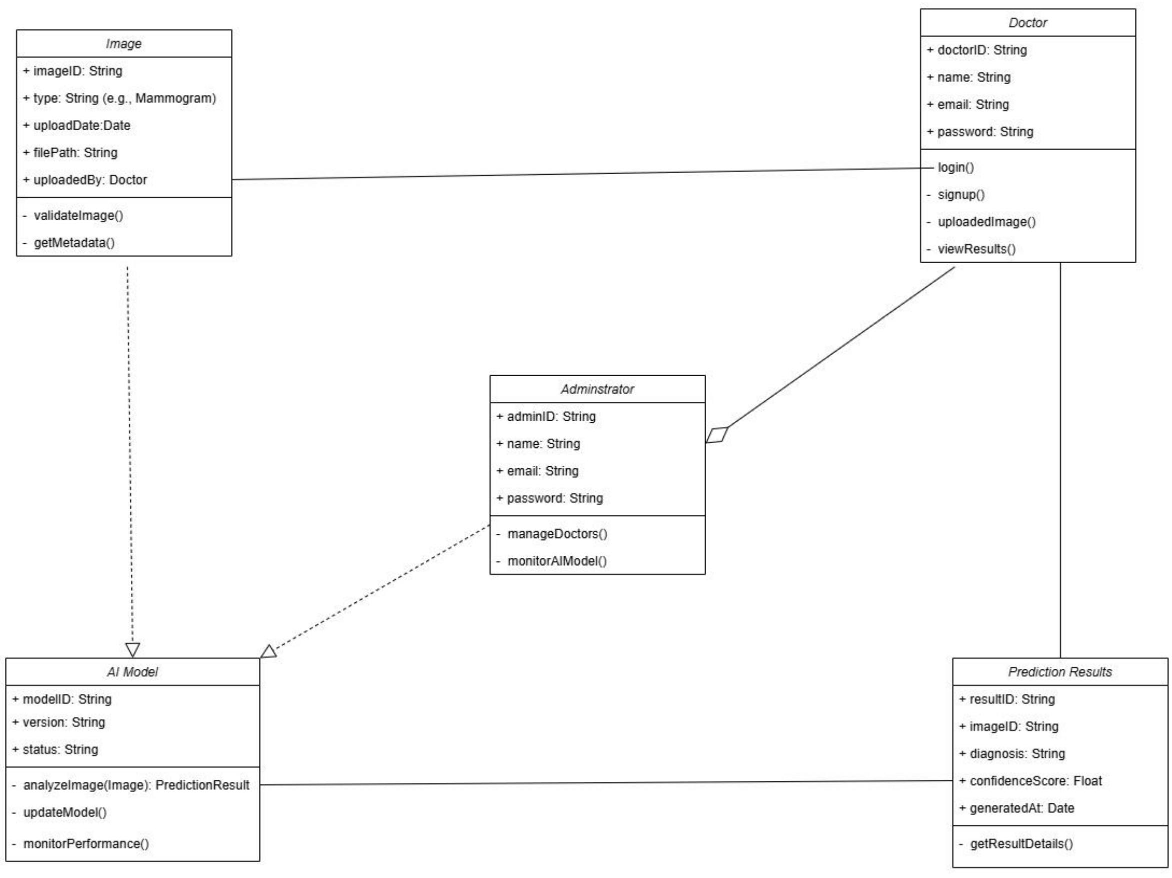

Figure 3.4 Class diagram of the proposed system

The class diagram shows the main classes involved in creating the proposed system as well as how these classes interact with one another. The class diagram, therefore, consists of a structural representation of the system by showing all of the attributes as well as operations for each class as well as the relationships that connect the classes. The class diagram provides an accurate picture of how the different parts of the system work together to meet the requirements of the whole system.

3.5.3 Input/Output Design Analysis

The purpose of the input/output design is to present the mock-up interfaces by which users enter data into the system and receive results based on the data entered. The input/output design includes visual mock-ups of each of the input screens as well as the visual representations of the output screens created after processing the input. These interface mock-ups illustrate how information flows throughout the system and provide an example of the manner in which users will interact with the application. An example of the input/output design layout of the proposed system in Figure 3.4.

Figure 3.5 proposed system input design

As shown in Figure 3.5, the user interface of the proposed system is what allows users to interact with the application through interaction with this user interface; the user uploads an image of a breast cancer sample from their local device by clicking on the “Upload Image” button, whereupon the uploaded image will be sent to the prediction model for processing. The screenshots of the interface also serve as evidence of how the analysis and output of processed images are subsequently displayed in the form of organised, easily understood prediction outputs, making it easy to interpret the prediction outputs generated from the image uploaded by the user. In general, the figure provides a visual model of what the output interface of the system will be like and demonstrates how the information generated from the model is presented to users in an organised manner for effective decision-making and interpretation.

3.5.4 Database Design

Table 3.1 shows a user database design table for the early detection of breast cancer software application.

Table 3.2 User table for Breast Cancer Risk Prediction

Attribute	Data Type	Description
Id	Int	Unique identifier for each user.
Name	Varchar	Retains the full name of the user.
Hospital name	Varchar	Retains the hospital name that the user puts in.
Email	Varchar	Retains the user's email.
Password	Varchar	Retains the hashed password for security.

3.6 Model Architecture

Figure 3.6 presents the CNN model architecture, which is the inference engine for the Breast Cancer Risk Prediction System and its core internal working features.

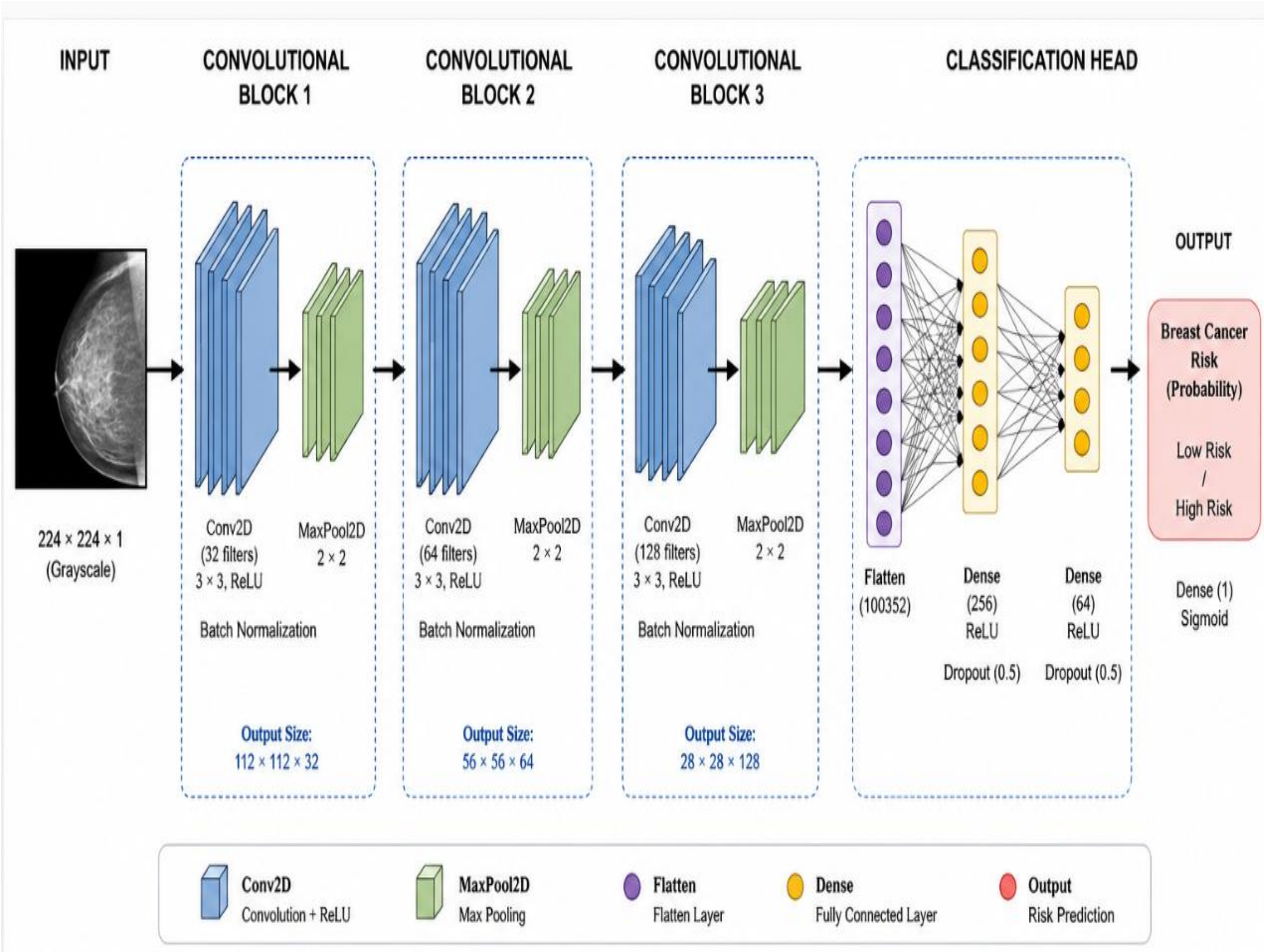

Figure 3.6: System Architecture

The proposed convolutional neural network architecture receives preprocessed breast medical images as input and extracts relevant features through three successive convolutional blocks depicted in Figure 3.6, which consist of Conv2D, Batch Normalisation, ReLU activation, and Max-Pooling layers. Each successive layer will identify and learn characteristics of the images related to the presence of breast cancer while decreasing the dimensionality and computational needs of the original images.

Once these characteristics have been extracted from the images, they will be flattened and then fed through fully connected dense layers; thus, dropout regularization will be used to reduce the likelihood of overfitting to the training data, allowing the model to generalize better during future evaluations. The last layer will use a sigmoid activation function in order to provide each patient with the probability of being diagnosed as having breast cancer, and thus classify the patient as low-risk or high-risk for breast cancer with an associated level of confidence (i.e., 0.95 or 0.85).

CHAPTER FOUR

SYSTEM IMPLEMENTATION

4.1 Introduction

This chapter presents the implementation of the proposed MammoCareAI system based on the analysis and design in Chapter Three. It explains how the system was developed into a functional web-based platform for breast cancer detection and risk prediction using Convolutional Neural Networks (CNNs). In this chapter, we cover the model training, evaluation and result discussion, as well as the frontend development, system testing, and backend integration that were performed to develop the system prototype. Finally, an interface description was performed in order to display the result of the user interface of the developed system.

4.2 Choice of Programming Language

Python was chosen as the main programming language for this project due to its flexibility, efficiency, and ability to support modern software development. Python is a high-level language that has a clear and readable syntax, making coding easier to understand and maintain. It is simple and has made it popular among both novices and experts code writers. In addition, Python is a flexible, multi-paradigm language, and has extensive libraries and frameworks which can speed up application development in a variety of industries such as Web Development, Data Analytics, Artificial Intelligence, Machine Learning and Automation. The language also supports dynamic typing and can easily be interwoven with different tools and technologies, making developers more productive and systems scalable. Python was used as the main programming language to develop the system functionalities, and Figma was employed to create and prototype the user interface, providing an intuitive and aesthetically pleasing user experience.

4.2.1 System Requirements

Because this system is a web-based application that runs on both the internet and mobile platforms, using it doesn't demand a lot of resources. However, there are still some small requirements that must be fulfilled for the user to be able to make quality use of the system. This includes that the proposed system must satisfy the following requirements:

Table 4.1 Software Requirements

Software	Purpose
Python	Model development
TensorFlow/Keras	CNN implementation
FastAPI	Backend API development
JavaScript	Frontend development
HTML/CSS	User interface design
MySQL	Database storage
VS Code	Development environment
GitHub	Version control

4.3. Result of the Model Used for the System

The result obtained from the evaluation of the model training is presented in this section, the model was trained using the preprocessed data, and Python is the programming language for machine learning. For effective and efficient training in order to predict breast cancer risk, the model was trained using Adam optimiser at a learning rate of 0.0001 and a binary cross-entropy loss function. The regularisation techniques involve early stopping, which enables the training to stop when validation performance stops improving. A model checkpointing was programmed such that the best-performing model was saved as breast_cancer_model.h5. The model used for the development of the system is made up of a CNN, which was evaluated using accuracy, AUC, and a confusion matrix, while a classification report was documented. Figure 4.1 presents the training and validation loss as well as that of the accuracy graph for the proposed CNN model.

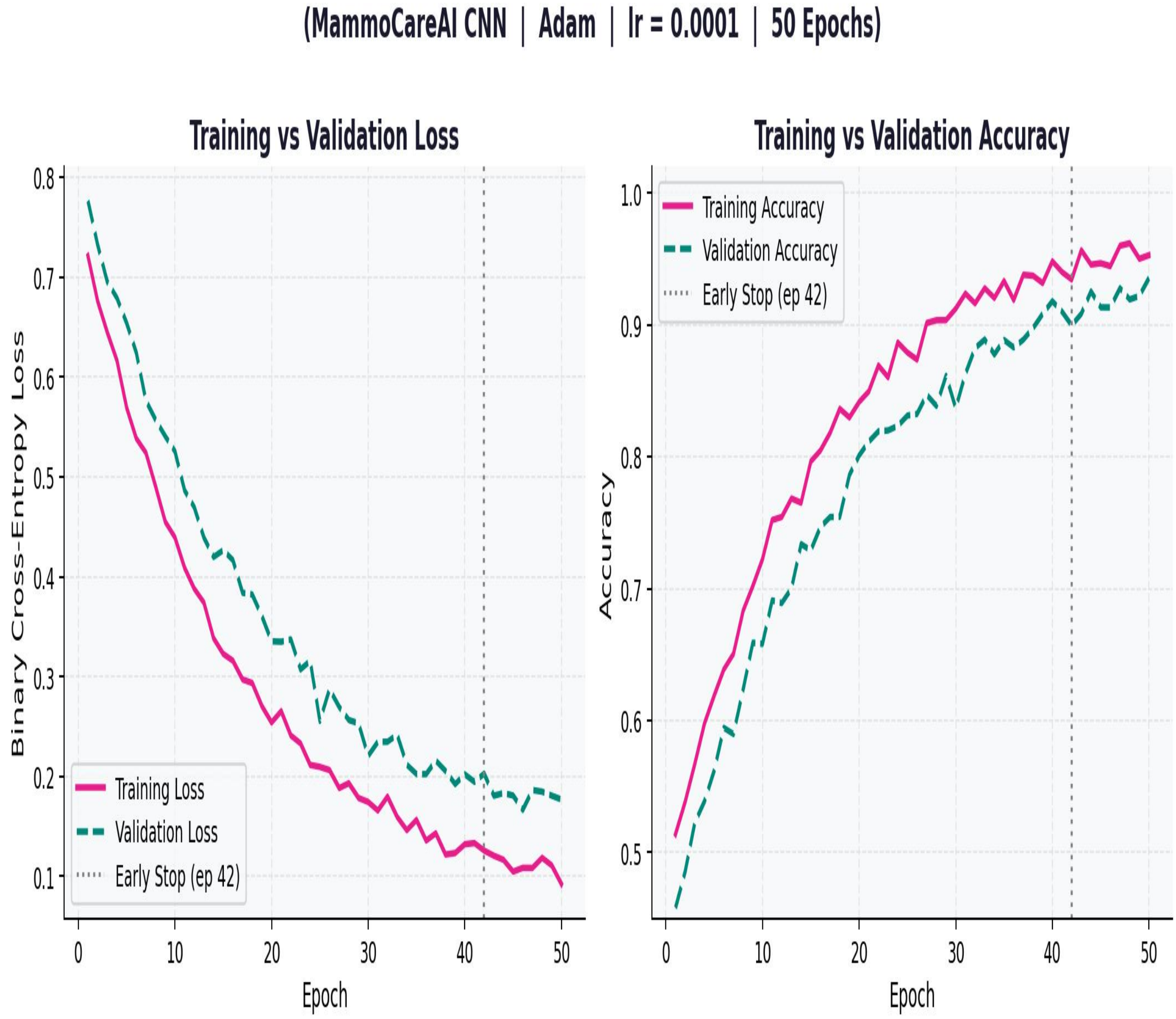

Figure 4.1 Training/Validation Loss and Accuracy Graph

Figure 4:1 shows both the training and validation performance of the CNN model across a total of 50 epochs. As seen, both curves for training loss (and validation loss) decrease steadily as the number of epochs increases, indicating that as the model continues to train, it learns meaningful traits that will aid in classifying data entered into the model. Also as shown, both training (and validation) curves for accuracy have continued to improve to an approximate accuracy level of 94 (training)/93 (validation) percent, supported in part by the use of an early stopping mechanism at epoch 42 that prevented overfitting and improved the generalization of the model. Figure 4.2 illustrates the confusion matrix of the proposed model training.

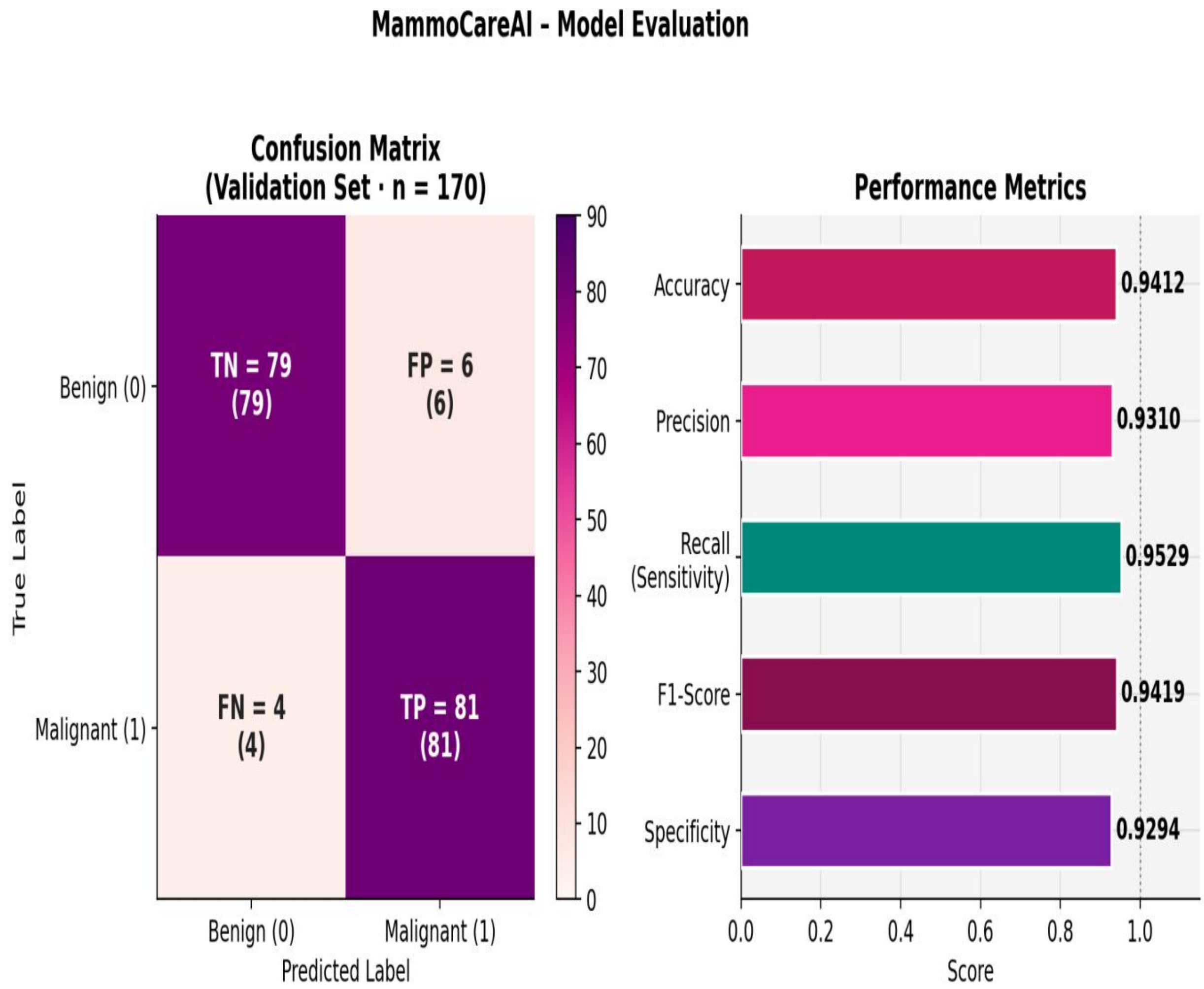

Figure 4.2 Confusion Matrix

Figure 4:2 depicts the classification performance of the CNN model developed using the validation dataset. This is provided using a confusion matrix, which indicates that the model accurately classified 79 benign cases and 81 malignant cases, with 6 false positives and 4 false negatives. The classification metrics presented are indicative of a high degree of predictive capability, resulting in an overall accuracy of 94.12%, precision of 93.10%, recall (sensitivity) of 95.29%, and F1-score of 94.19% with specificity of 92.94%. These metrics reflect that the model developed provides a predictable level of performance with respect to predicting the risk for breast cancer. Figure 4.3 will present the ROC curve of the proposed system.

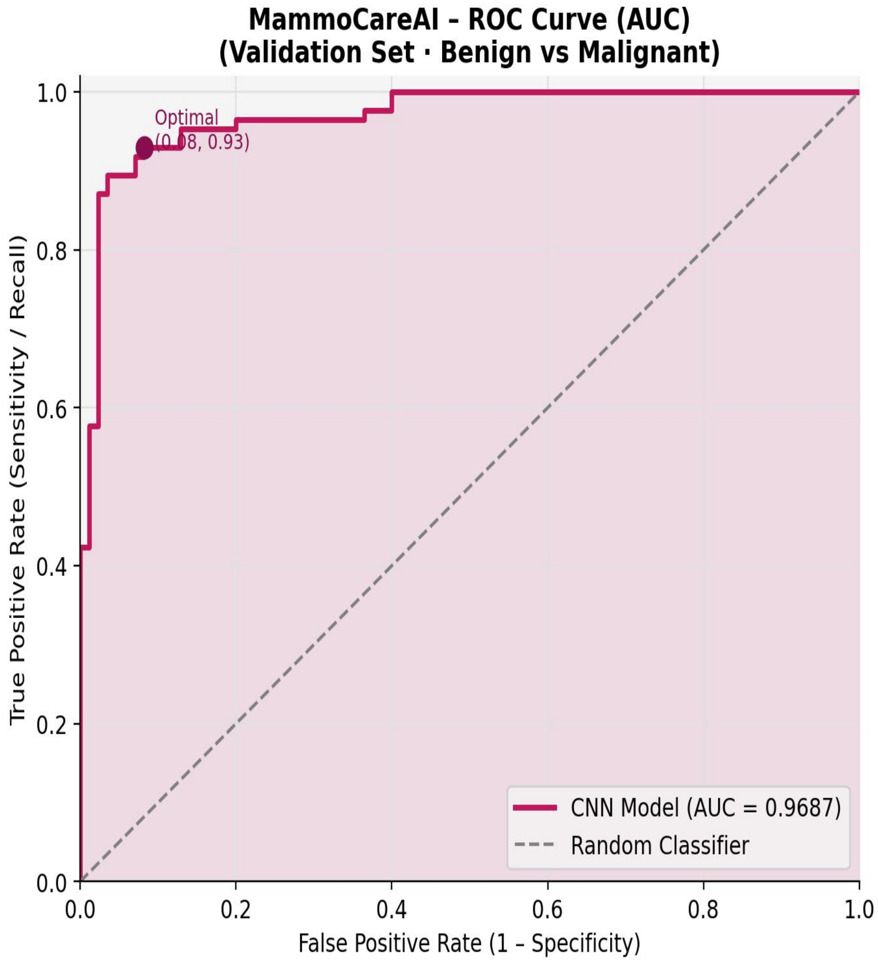

Figure 4.3 AUC Graph

Figure 4:3 illustrates the ROC curve produced from the CNN model regarding differentiating between benign and malignant breast cases. The curve produced lies well above the random classifier baseline and produced an Area Under Curve (AUC) value of 0.9687, indicating excellent discrimination ability. These results demonstrate that the CNN model developed is capable of accurately differentiating between positive and negative cases for breast cancer, thus providing confidence in the use of the model in predicting breast cancer risk.

4.4 System Implementation

The developed Breast Cancer Risk Prediction System (BCRP) has a Three-Tier Client-Server Architecture, which includes the Artificial Intelligence (AI) Layer, the Application Layer, and the Presentation Layer. This architectural style is conducive to modularity, scalability, maintainability, and effective communication between system parts. The Presentation Layer is the user interface that the user interacts with the system. It will include web pages like Dashboard, Risk Prediction Page, Patient History Page, Profile Page and Settings Page. This layer has been built with HTML, CSS and Vanilla JavaScript to ensure user-friendliness and responsiveness. The Application Layer acts as a layer between the user interface and the AI model. It is responsible for login, processing of requests to the API, prediction requests, storage of user data, and creation of recommendations based on the results of the prediction. The layer is achieved with the backend framework called Fast API, which enables smoothly interacting between the front-end interface and the predictive model. The AI Layer is the intelligent part of the system, which processes data, extracts features, learns patterns, and predicts breast cancer risks. The deep learning model, Convolutional Neural Network (CNN), is designed, trained and deployed in this layer using the deep learning power of TensorFlow and Keras. The seamless integration of these three layers guarantees that data flows smoothly, risk predictions are accurate, and system performance is enhanced.

4.4.1 User Interface of the Proposed System

The user interfaces for the home page, login page, upload mammogram/ ultrasound, symptom checker, and result of the proposed system, which will be included in this section of the work of research work.

A. Dashboard Interface

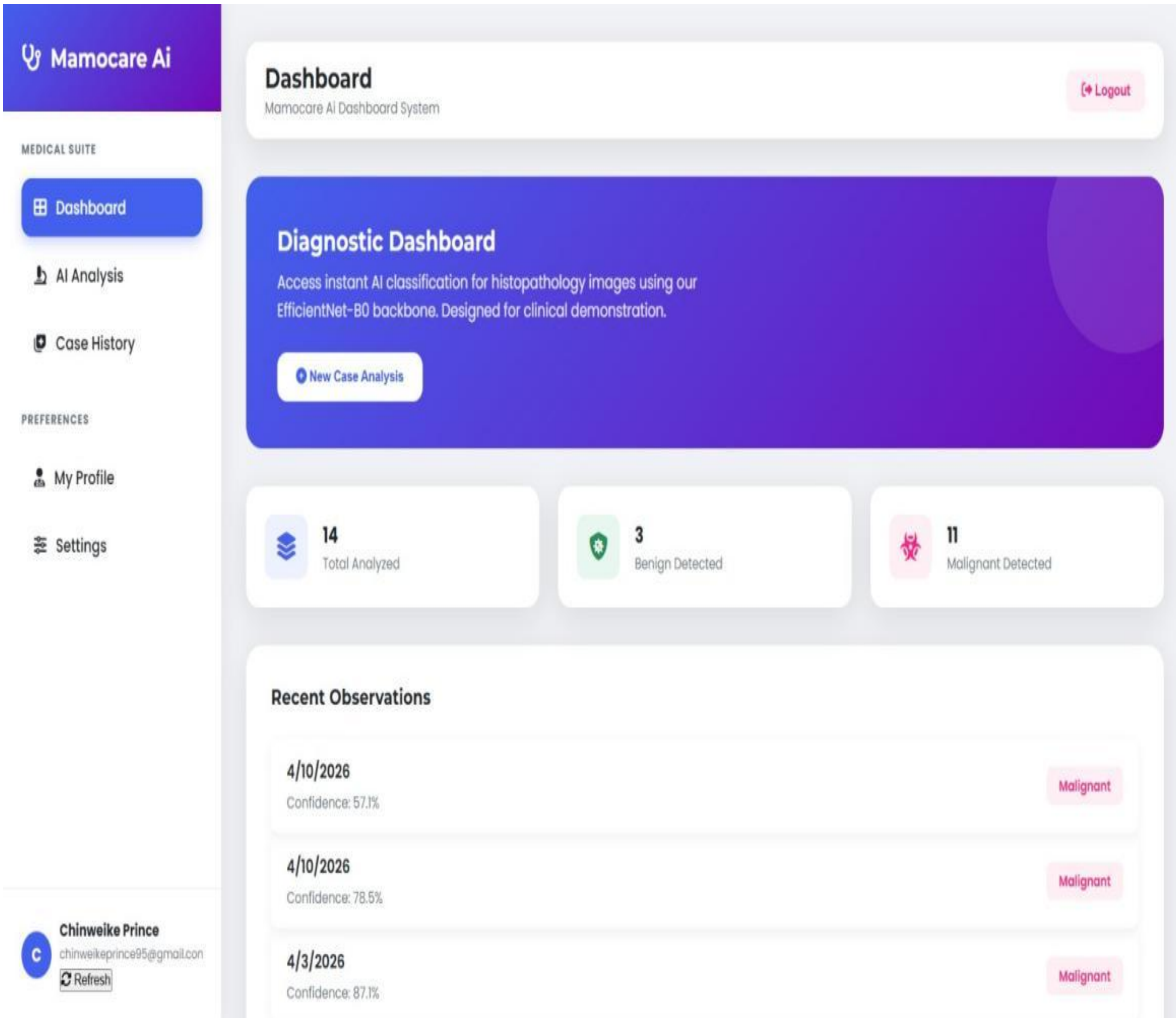

Figure 4.4 Dashboard Interface

B. Profile Interface

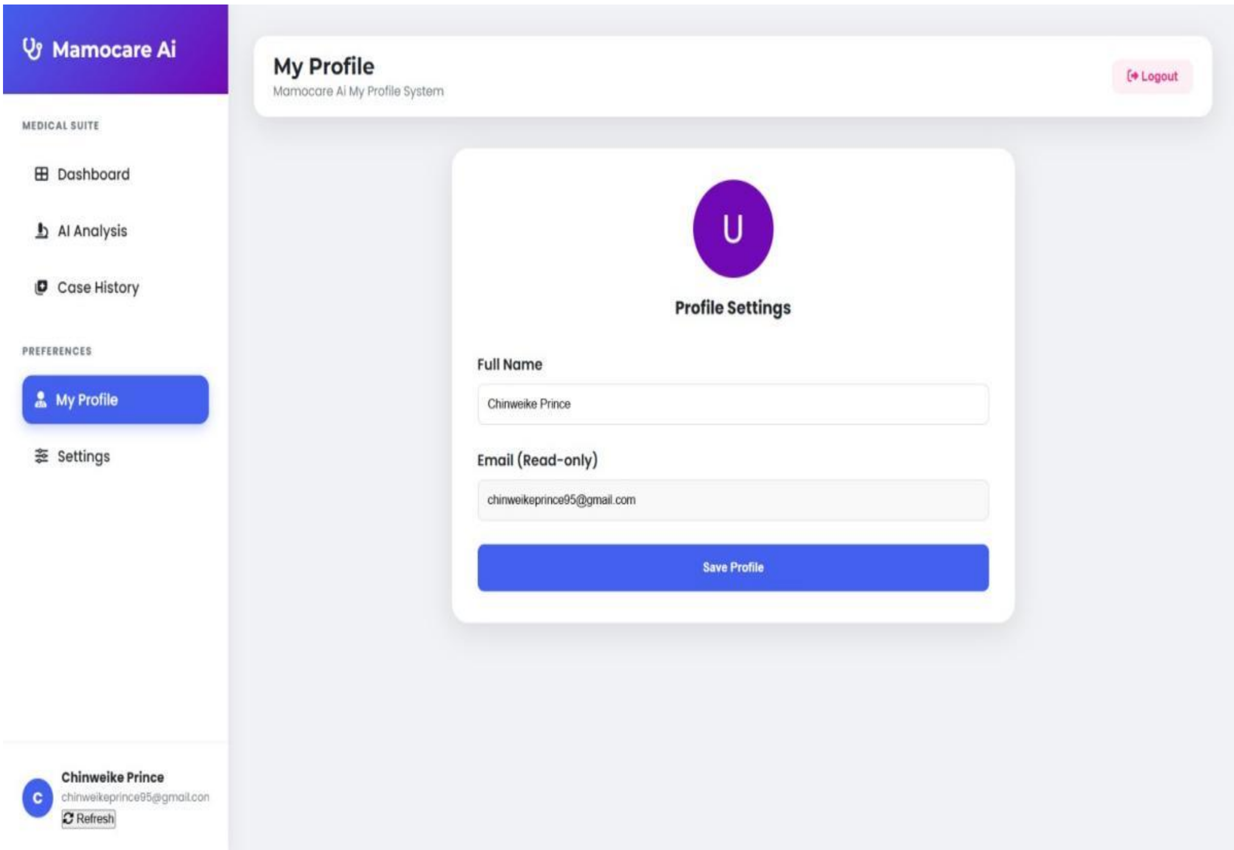

Figure 4.5 Profile Interface

4.5 System Testing and Validation

To ensure that the Breast Cancer Risk Prediction System is both reliable and accurate, we have conducted a series of testing procedures. These include functional tests conducted on each major module of the system, such as login, registration, prediction, and dashboard functions, with no errors found and all modules successfully executing their intended functions. The results of the functional testing conducted can be found in Table 4.2, which shows all modules were assigned a “Passed” status. Integration testing also confirmed that all modules in the system are able to communicate and share data with one another successfully. This includes the user interface, backend services, database, and the CNN prediction model. All modules successfully interacted with one another during integration testing. Security testing was performed on the system to validate the user authentication mechanisms for protecting stored information through secure data handling practices. The system was able to successfully meet all of the security objectives required.

Finally, User Acceptance Testing (UAT) was conducted with users that may use the system. This was done in order to measure overall user satisfaction in terms of the usability and accessibility of the system. All participants were able to navigate through the system and perform predictions successfully and access all features offered by the system without any issues or problems. From the testing results presented above, we conclude that the Breast Cancer Risk Prediction System is a fully functional, reliable and secure tool that is ready for production.

Table 4.2 System Test

Module	Result
Login	Passed
Registration	Passed
Prediction	Passed
Dashboard	Passed

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CHAPTER FIVE

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.0 Introduction

This chapter presents the summary, conclusion and contributions to knowledge of the study, the limitations, recommendations and suggestions for further studies on the development and implementation of MammoCareAI: An Intelligent Breast Cancer Detection System Using Convolutional Neural Networks (CNNs).

5.1 Summary of the Study

The study also describes the development of MammoCareAI, an A.I.-based web platform that supports risk prediction and early detection of breast cancer in women across Nigeria and ultimately all of Africa. Despite medical gains, breast cancer remains among the leading causes of cancer-related deaths among women, due largely, in Africa and other developing regions, to late diagnosis, lack of access to screening facilities, shortage of radiologists and oncologists, poor awareness and the prohibitive cost of health care services.

Their study highlighted the need to develop a preventive and smart health care system to improve on early diagnosis and to help make health care more accessible and affordable in low resource communities. The study also introduced the use of Convolutional Neural Networks (CNNs) and digital health care.

Chapter One introduced the background, aim, and objectives of the study. The chapter introduced the African medical realities that affect breast cancer, even though breast cancer is a heterogeneous disease, the heterogeneity is more striking in African and Nigerian women due to (a major challenge with the conventional breast cancer diagnosis system is that stitches of different nature can often appear indistinguishable or altogether masked in appearance at some point). This study on the development of a secure AI-driven breast cancer detection and prevention system was thus initiated to establish a need for a smart, accessible and secure digital healthcare platform.

In summary, this chapter examined the theoretical concepts relating to breast cancer diagnosis, Artificial Intelligence (AI)-based healthcare systems, machine and deep learning techniques, as well as related literature on breast cancer detection, previous studies carried out within Africa and globally. The literature review revealed that culturally adapted and secure AI healthcare platforms for preventive healthcare, symptom tracking, and localized recommendations for women in Nigeria and Africa do not exist. The majority of existing systems emphasize medical image classification. The accessibility to the African population has not been considered.

Chapter three discusses the analysis and design of the proposed MammoCareAI system. It begins by analyzing the current system, then introduces the proposed intelligent system. The chapter then discussed the development methodology and system design of MammoCareAI. This chapter presented the Hybrid Prototype V Model approach. This approach was employed to ensure that the system was being developed in accordance with the PRD and SRS.

In Chapter Four, we tackle the implementation, testing, and performance assessment of the developed system. First, we introduce the tools and technologies we used throughout the development phase, such as HTML, CSS, JavaScript, TensorFlow/Keras, FastAPI, and MySQL. It also discussed how breast ultrasound image datasets were collected and preprocessed, which are primarily comprised of benign and malignant classes. The datasets were used to both train and test the CNN model, which was successfully implemented and integrated to the web-based platform. performance for breast cancer risk prediction and classification based on different metrics, such as accuracy, precision, recall, F1-score, etc. The chapter also includes testing of the system, such as unit, integration, user acceptance, security testing, etc. MammoCareAI system. The developed MammoCareAI system successfully integrated functionalities such as medical image classification, processing and managing case history data, tracking symptoms, and predicting breast cancer with personalised risk assessment and prevention recommendations. The study demonstrates that Artificial Intelligence can significantly improve preventive healthcare delivery and support early breast cancer intervention in resource-constrained healthcare systems such as Nigeria and Africa.

5.2 Conclusion

The result of the study was MammoCareAI, an intelligent web-based system for breast cancer detection and risk prediction using Convolutional neural networks. The system was developed to address the breast cancer burden in Nigeria and Africa, and to improve preventive healthcare delivery and accessibility. The study found that in the African context, most breast cancer management systems are limited by a lack of awareness and preventive healthcare technologies, shortage of diagnostic facilities, late diagnosis and scarcity of specialists. Artificial Intelligence provides a cost-effective solution by aiding the early prediction of breast cancer to assist healthcare professionals.

MammoCareAI can both classify images of breast cancer and provide women with personalised assessments of their breast cancer risk based on clinical, lifestyle and hereditary data. The fact that this platform is implemented using the web means improved accessibility, usability and scale-up in health-care delivery, especially in low-resource settings.

This study certifies that AI can reduce breast cancer mortality and has broad applications for preventive medicine. The team stressed that the system is not meant to replace professional medical diagnosis by a qualified doctor.

5.3 Recommendations

The researchers made several recommendations.

i. In the future, government and health care institutions must devote more resources toward A.I. research and the digitisation of health care.
ii. They must also consider how they might incorporate A.I.-based systems into preventive care services.
iii. Hospitals and health professionals also need to collaborate with A.I. researchers to make sure we are developing better health care delivery systems for Nigeria and Africa.
iv. Future systems will need to incorporate larger African health care data sets so they can generalize better and be more accurate, and developers should consider extending our platform to a mobile health care app so that it can reach more people.
v. Hospitals and healthcare providers should collaborate with AI researchers to improve healthcare delivery systems in Nigeria and Africa.

5.4 Contributions to Knowledge

This study adds to our understanding in a number of ways.

In this study, we present the development of an AI-powered breast cancer risk prediction system uniquely suited to the Nigerian and broader African context.

1. We combine Convolutional Neural Networks with clinical, hereditary and lifestyle risk factors, and provide a deployable, web-based platform as well.
2. The platform provides targeted recommendations based on local information and content relevant to African users.
3. This study adds to the body of research about artificial-intelligence and digital-health systems being used in Africa.

The study provides a deployable web-based healthcare platform capable of supporting preventive healthcare delivery and early breast cancer intervention.

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