BINDURA UNIVERSITY OF SCIENCE EDUCATION
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Deep Learning Based Breast Cancer Detection Using MRI Images

By
Vaida Kadzombe
B191548B

SUPERVISOR: Mr Chaka

A RESEARCH PROJECT SUBMITTED TO THE COMPUTER SCIENCE DEPARTMENT IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE BACHELOR OF SCIENCE HONOURS DEGREE IN COMPUTER SCIENCE.

Approval Form

The undersigned certify that they have supervised the student Vaida Kadzombe in the research dissertation entitled, "**Deep Learning Based Breast Cancer Detection Using MRI images**" submitted in partial fulfilment of the requirements for a Bachelor of Science Honors Degree in Computer Science at Bindura University of Science Education.

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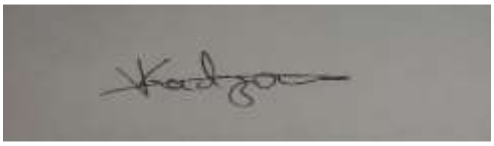

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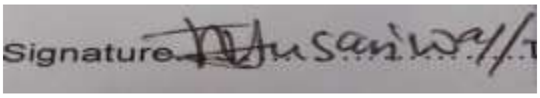

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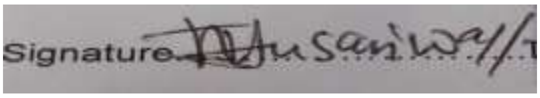

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Abstract

Breast cancer represents a critical global health issue, underscoring the importance of early detection to enhance treatment efficacy and increase survival rates. It is characterized by the uncontrolled growth of abnormal cells in the breast, leading to the formation of tumors. If not promptly addressed, these tumors can metastasize, posing a fatal risk. Breast cancer typically originates within the milk ducts or the milk-producing lobules of the breast. Utilizing advancements in deep learning and artificial intelligence presents an opportunity to enhance breast cancer detection methods. This study proposes the utilization of a deep learning system to identify breast cancer through the analysis of MRI images. It describes the goals, methods, and expected results. Breast cancer is a prevalent issue for women worldwide, causing considerable healthcare and financial challenges for Zimbabwe. Despite various detection methods, challenges persist, including delayed healthcare seeking and limited access to early detection facilities. Deep learning techniques offer promise in diagnosing breast cancer earlier and more accurately, particularly when integrated with MRI imaging. Such methods require less human intervention and can detect abnormalities that may be missed by conventional procedures. The proposed system employs advanced neural network architectures to analyze MRI images, automatically extracting features indicative of breast cancer lesions. Preliminary testing indicates promising results, with an accuracy rate of 93.6% surpassing comparable works in the literature. Future enhancements may involve utilizing more powerful computational machines, augmenting training data, and striking a balance between precision and recall to optimize model performance. By integrating these recommendations, this research aims to advance breast cancer detection, ultimately contributing to improved patient outcomes and personalized healthcare.

Keywords: Breast Cancer, Convolutional Neural Network, Tumor, Abnormalities, MRI images, Deep Learning

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CHAPTER 1

PROBLEM DEFINITION

1.1 Introduction

Breast cancer remains a significant global health challenge, impacting numerous individuals annually. Early detection is critical for effective treatment and improving survival rates. The advancement of deep learning and artificial intelligence offers promising opportunities to enhance breast cancer detection methods. This research paper outlines the objectives, methodologies, and anticipated outcomes of a study focused on developing a deep learning-based system for breast cancer detection. It's noteworthy that breast cancer is the most prevalent cancer among women worldwide (Sani et al., 2020). In Zimbabwe, it poses a considerable burden on the healthcare system and can be financially devastating for patients, who often bear the majority of treatment costs (Kadzatsa & Ndarukwa-Jambwa, 2019). Indeed, breast cancer is a significant global health concern (Borkar et al., 2015) and is a leading cause of cancer-related deaths among women globally (Azubuike & Okwuokei, 2013). Notably, breast cancer affects not only women but also men and even animals, although only 1% of cases occur in men (Benson et al., 2009; Beg & Jain, 2012).

1.2 Background of the study

Breast cancer is a significant global health concern, particularly impacting women, and remains the leading cause of death among women. Despite its prevalence, a definitive cure for breast cancer has not been found. In Zimbabwe, breast cancer is the second most common cancer among women, with high mortality rates due to delayed healthcare seeking. The country also faces challenges associated with HIV-related breast cancer cases. Many Zimbabwean women delay seeking medical care due to fear of community reactions and the potential loss of a breast. Doctors employ various tests, including mammography, ultrasound, MRI, and biopsy, for breast cancer detection. While mammography is commonly used, it has limitations such as age restrictions, poor performance in dense breast tissue, and discomfort. MRI has shown promise in detecting small breast lesions missed by mammography and is particularly useful for younger women with dense breast tissue. Deep learning methods have demonstrated the ability to diagnose breast cancer earlier than conventional procedures, and utilizing MRI images with deep learning algorithms can aid in early detection and improve accuracy, thereby increasing survival rates. Notably, deep learning requires less human intervention compared to traditional machine learning techniques.

1.3 Problem Statement

According to the Ministry of Health and Child Care (MoHCC, 2018), early diagnosis and screening programs are essential in enhancing treatment success rates, as many cancers have the highest likelihood of being cured when identified at an early stage. Screening is crucial in saving lives and reducing the expenses associated with treating advanced disease. However, national cancer screening programs are still in their early stages due to limited access to early detection facilities and a shortage of human resources and technology, which negatively impacts early cancer diagnosis (MoHCC, 2018). Therefore, while there is no prevention mechanism for breast cancer, early detection can significantly improve outcomes and considerably reduce treatment costs. Employing MRIs is indispensable for detecting any early irregularities before the tumor advances.

1.4 Research Aim

- To assess the use of deep learning in the Detection of Breast Cancer on MRI Images.

1.5 Research Objectives

1. To analyse different deep learning techniques used for breast cancer detection.
2. To design and implement a deep learning model which detects breast cancer using deep convolutional neural networks (DCNN).
3. Evaluate the effectiveness of DCNN in breast cancer detection and diagnosis.

1.6 Research questions

The study addresses the issues outlined in the problem statement by answering the following questions:

- How can the accuracy of breast cancer diagnosis using MRI images be enhanced through the use of deep learning models?
- What are the essential factors to consider when designing and implementing a deep learning model for breast cancer diagnosis using deep convolutional neural networks (DCNN)?

- How does the performance of the DCNN model compare to other established methods in terms of accuracy, sensitivity, specificity, and AUC-ROC for detecting and diagnosing breast cancer?

1.8 Justification/Significance of the study

- Improving Breast Cancer Outcomes: Breast cancer ranks as a primary contributor to cancer-related fatalities among women in Zimbabwe. Timely detection remains pivotal for successful treatment outcomes. This study holds promise for enhancing the precision and promptness of breast cancer diagnosis, thereby enhancing survival rates and alleviating the strain on the healthcare system.
- Limited Healthcare Resources: Zimbabwe, like many other developing nations, faces resource constraints in its healthcare system. Deep learning-based detection tools can help optimize resource allocation by identifying high-risk cases early, allowing healthcare providers to focus their efforts and resources on those in need.
- Reducing Healthcare Costs: Breast cancer treatment is costly, and late-stage diagnosis often results in more extensive and expensive interventions. A more efficient and accurate early detection system can help reduce the economic burden on both patients and the healthcare system.
- Access to Specialized Expertise: Zimbabwe faces challenges in accessing specialized medical expertise, particularly in rural areas. Deep learning models can be deployed in telemedicine applications to bridge the gap, allowing patients in remote regions to benefit from advanced diagnostic tools.
- Capacity Building: Conducting this research in Zimbabwe provides an opportunity to build local expertise in AI and deep learning applications in healthcare. This can lead to the development of a skilled workforce capable of addressing various healthcare challenges beyond breast cancer detection.
- Global Collaboration: The global research community is actively involved in the development of AI-based healthcare solutions. By participating in this research, Zimbabwe can benefit from international collaborations, knowledge sharing, and access to state-of-the-art technology.
- Improved Women's Health: As breast cancer primarily affects women, this research directly contributes to improving women's health and well-being in Zimbabwe. It underscores the importance of addressing gender-specific health issues.

- Public Awareness: The research study also offers an opportunity to raise awareness regarding breast cancer, emphasizing the importance of early detection and the integration of AI in healthcare. Heightened awareness has the potential to motivate women to undergo regular screenings, facilitating earlier diagnosis.

1.9 Assumptions

- The MRI images used in the study are of sufficient quality and resolution to extract meaningful features for breast cancer detection.
- Having access to a suitably extensive and representative dataset of labeled MRI images for training and assessing the deep learning models.
- The annotations or labels provided for the MRI images are accurate and reliable, representing the ground truth for breast cancer presence or absence.
- The computational resources and infrastructure required to train and evaluate deep learning models on large-scale MRI datasets are available and sufficient.
- The ethical and regulatory considerations related to the use of patient data and the deployment of deep learning models in clinical settings have been addressed, ensuring patient privacy, informed consent, and compliance with relevant regulations.

1.10 Limitation/Challenges

- Implementing all the system's functional requirements may take longer than expected.
- Finding experts to collaborate on the project could be challenging.
- It might be difficult to acquire the informed consent and compliance with relevant regulations to use patient data

1.11 Scope/Delimitation of the Research

The aim of this study is to develop a deep learning-based system to assist in diagnosing breast cancer using MRI images. The focus is specifically on MRI images, excluding other detection techniques such as mammography, breast ultrasound, or biopsy. This approach is intended to improve the accuracy of results and facilitate the early diagnosis of breast tumors.

1.12 Definition of terms

Breast Cancer: Breast cancer, a malignant tumor that develops from breast tissue cells, initiates when cells within the breast undergo uncontrolled growth, leading to the formation of a tumor and subsequently causing breast cancer (Irvin and Carey, 2008).

Machine Learning: the field of study focused on enabling computers to perform tasks and make decisions without explicit programming (Alpaydın, 2014).

Mammography: is a type of X-ray image of the breasts, which is commonly used for breast screening or to explore symptoms or unusual results found on other imaging tests.

Breast Ultrasound: Breast ultrasound is an imaging test that uses sound waves to examine the internal structures of the breasts (Johns Hopkins, 2021).

Breast Biopsy: is a procedure where tissue or fluid is taken from the breast for microscopic examination and further testing. Various types of biopsies exist, such as fine-needle aspiration, core biopsy, or open biopsy.

Deep learning: is a subset of machine learning that employs multi-layered neural networks to identify and extract intricate patterns and features from extensive datasets (LeCun, 2015).

Deep Convolutional Neural Network (DCNN): is a type of deep learning architecture specifically designed for processing visual data, such as images. It employs convolutional layers to capture local patterns and spatial relationships (Krizhevsky et al., 2012).

Magnetic Resonance Imaging (MRI): is a medical imaging method that employs a powerful magnetic field and radio waves to create detailed, high-resolution images of the body's internal structures. It is especially effective for visualizing soft tissues and organs (Kanal et al., 2013).

CHAPTER 2

LITERATURE REVIEW

2.1.0 Introduction

A review of the literature as per Booth, Papaioannou, and Sutton (2016), involves systematically summarizing and analyzing existing research on a specific topic. In this chapter, the researcher delves into addressing the research questions and uncovering prior and contemporary systems resembling the current research project carried out by other scholars. It will survey recent advancements in deep learning architectures, methodologies, and techniques applied to the analysis of breast MRI data for early detection and diagnosis of breast cancer. Additionally, the review will address the challenges, limitations, and future directions in the field, with a focus on identifying key research gaps and opportunities for further innovation.

Breast cancer is recognized as one of the most common and life-threatening diseases impacting women globally (Bray et al., 2018). Timely detection and precise diagnosis are imperative for improving patient results and decreasing mortality rates linked with breast cancer (Howlader et al., 2020). Recent advancements in medical imaging technologies, combined with the emergence of deep learning methodologies, have transformed the landscape of breast cancer detection and diagnosis (Esteva et al., 2019). Magnetic resonance imaging (MRI) has emerged as a potent tool for assessing breast cancer, providing high-resolution, multi-dimensional images that offer valuable insights into breast morphology and tissue characteristics (Orel and Schnall, 2001). The detailed information captured by breast MRI scans, including spatial and temporal dynamics, renders it invaluable for detecting subtle abnormalities indicative of breast cancer (Kuhl, 2007). Deep learning, a subset of artificial intelligence (AI) that utilizes multi-layered neural networks to automatically learn hierarchical representations of data, has demonstrated significant promise in medical image analysis, particularly in breast cancer detection (LeCun et al., 2015). By effectively capturing intricate patterns and relationships within medical images, deep learning models have the potential to improve the accuracy, efficiency, and reliability of breast cancer diagnosis (Shen et al., 2017).

2.1.1 Breast Cancer

Breast cancer is defined by the World Health Organization (2023) as the abnormal proliferation of breast cells, resulting in tumor formation. If left unmanaged, these tumors can metastasize, posing life-threatening risks. Primarily, breast cancer originates from either the milk ducts or the glands responsible for milk production within the breast tissue (World Health Organization, 2023). Tumors in the breast can manifest as either benign or malignant. According to the Mayo Clinic (2022), benign tumors comprise non-cancerous cells that do not invade nearby tissues or metastasize. Although they may cause symptoms depending on their location, benign tumors do not pose significant health risks. Conversely, malignant tumors contain cancer cells with the potential to invade surrounding tissues and spread to other parts of the body, a process known as metastasis (Mayo Clinic, 2022). Considered cancerous, malignant tumors can lead to serious health complications if not treated promptly.

2.1.2 Types of Breast Cancer

There exist four primary types of breast cancer, highly prevalent among them and these are:

Ductal Carcinoma In Situ (DCIS):

Ductal carcinoma stands as the predominant form of breast cancer, comprising roughly 80% of all cases (American Cancer Society, 2021). Ductal carcinoma in situ (DCIS) represents a subtype of breast cancer originating within the milk ducts, characterized by its non-invasive nature, as it does not infiltrate surrounding tissues (National Breast Cancer Foundation, 2022). Moreover, DCIS remains confined within the ductal system and has not extended beyond it.

Invasive Ductal Carcinoma (IDC):

IDC, another prevalent form of breast cancer, constitutes about 70-80% of cases. It begins in the milk ducts but infiltrates surrounding breast tissue. (National Breast Cancer Foundation, 2022).

Invasive Lobular Carcinoma (ILC):

ILC originates in the lobules or milk-producing glands of the breast, comprising a smaller proportion of breast cancer cases compared to ductal carcinoma approximately 10-15% of invasive breast cancers (National Breast Cancer Foundation, 2022).

Triple-Negative Breast Cancer (TNBC):

TNBC is identified by the lack of estrogen receptor (ER), progesterone receptor (PR), and human epidermal growth factor receptor 2 (HER2) expression and constitutes approximately 10-15% of breast cancer instances (National Breast Cancer Foundation, 2022).

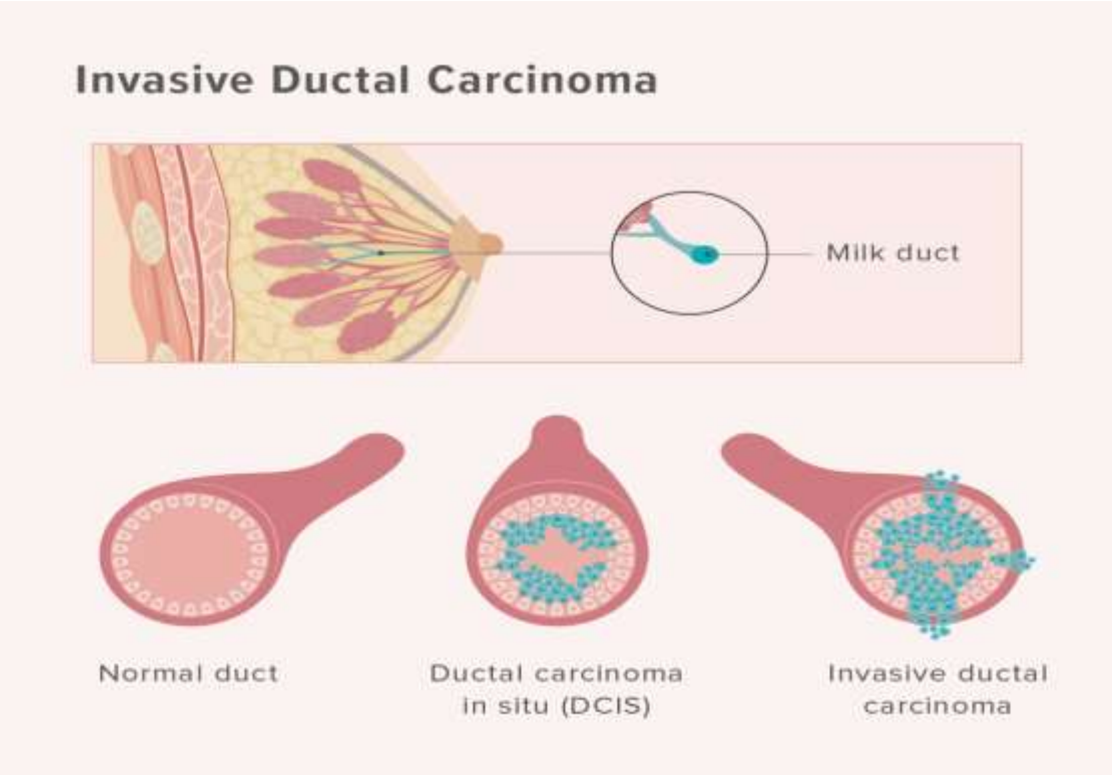

Figure 1: Breast Cancer

2.1.3 Symptoms

Breast cancer often shows up as a lump in the breast or armpit. It's good to check your breasts regularly to know how they usually feel and look. Some signs of breast cancer include swelling or a lump in the breast, swollen armpit glands, nipple discharge, nipple pain, nipple turning inward, rough or pitted nipple skin, ongoing breast tenderness, and unusual breast pain. In later stages, breast cancer may metastasize to other parts of the body, causing symptoms like bone pain, trouble breathing, loss of appetite, unintentional weight loss, headaches, and nerve pain or weakness (Mayo Clinic, 2023; Stephan, 2010).

2.2 Breast Cancer in Zimbabwe

Breast cancer has become increasingly prevalent worldwide, including in Zimbabwe, where it is the most prevalent cancer among women. According to the Zimbabwe National Cancer Registry, breast cancer accounts for a significant portion of newly diagnosed cancers in the country. Unfortunately, limited resources and barriers to healthcare access result in late-stage diagnoses, leading to higher mortality rates (Elsie Gotora, 2021). In Zimbabwe, breast cancer constitutes 12.4% of cases among black women, contributing to significant morbidity and mortality. Factors such as advancing age, family history of breast cancer, genetic mutations (such as BRCA gene), reproductive factors, obesity, and lifestyle choices are known to contribute to breast cancer development in Zimbabwe. Additionally, the HIV and AIDS epidemic in the country further adds to the breast cancer burden, as HIV infection is often associated with breast cancer cases (Chokunonga, 2016).

Despite the increasing prevalence of breast cancer, screening coverage and accessibility to screening services in Zimbabwe remain limited. Late detection is common due to various reasons, including misconceptions about cancer, lack of awareness, and limited availability of early detection services. A considerable number of cancer patients in Zimbabwe seek healthcare at advanced stages (stage 3 and 4), leading to higher premature deaths (Nkala, 2014). Lack of knowledge about breast cancer is a significant factor contributing to delayed healthcare-seeking behavior, as shown by studies indicating that a significant portion of the population in Zimbabwe has limited awareness of breast cancer (Muchirevesi, 2016). Fear of community rejection and loss of a breast are additional factors that discourage women in Zimbabwe from seeking timely healthcare for breast cancer. Economic hardships in the country also affect healthcare systems, including service delivery and affordability of healthcare services (Nyakabau, 2014). Socio-economic factors significantly contribute to delays in accessing healthcare for breast cancer in Zimbabwe (Elsie Gotora, 2021).

Despite the implementation of health promotion materials and awareness campaigns targeting breast cancer risk factors and self-examination, the disease remains a significant public health concern for women in Zimbabwe, with late presentations to healthcare providers at advanced stages (stage 3 and 4) being a primary challenge due to limited curative treatment options (Elsie Gotora, 2021). According to 2020 GLOBOCAN data, Africa reported 186,598 breast cancer cases with 85,787 related deaths. While Sub-Saharan Africa (SSA) exhibits a lower disease burden, survival rates are notably low, contributing to elevated mortality rates. The period from 2005 to 2015 saw a doubling of breast cancer incidence from 1.2 to 2.4 million cases, attributed to population growth and aging. A recent report indicates a rising trend of breast cancer across Africa, with projections suggesting a doubling by 2050. Globally, female breast cancer surpasses lung cancer as the most common diagnosis, with an estimated 2.3 million new cases and 685,000 deaths reported in 2020 alone. By the end of the same year, 7.8 million women worldwide were living with a breast cancer diagnosis from the past 5 years, cementing its status as the most prevalent cancer globally. Breast cancer affects women across all countries, typically manifesting after puberty and exhibiting an increasing incidence with age.

2.3 Early Breast Cancer Detection

Early breast cancer detection is pivotal in enhancing patient outcomes and diminishing mortality rates linked with the disease. Identifying breast cancer at an early stage allows for timely intervention and treatment, which can significantly increase the chances of successful treatment and survival. Screening methods such as mammography, clinical breast examination, breast MRI imaging, and breast ultrasound are commonly used for early detection of breast cancer (American Cancer Society, 2021). Mammography, in particular, is considered the gold standard for breast cancer screening, as it can detect abnormalities in the breast tissue, such as tumors or calcifications, before they can be felt during a physical examination (National Cancer Institute, 2022). Additionally, breast MRI imaging and breast ultrasound are valuable tools for detecting breast cancer, particularly in women with dense breast tissue or those with a heightened risk of the condition. MRI imaging provides high-resolution, multi-dimensional images that offer valuable insights into breast morphology and tissue characteristics, while ultrasound uses sound waves to create images of the breast tissue, aiding in the detection of abnormalities (Orel & Schnall, 2001; Kuhl, 2007). Early detection enables healthcare providers to diagnose breast cancer at a localized stage when it is most treatable, often leading to less aggressive treatment and better long-term outcomes for patients (American Cancer Society, 2021).

2.4 Machine Learning

According to Emerj Artificial Intelligence Research (2021), machine learning involves teaching computers to learn and behave similarly to humans, progressively improving their learning capabilities autonomously through the input of data and information derived from observations and real-world interactions. Koza, Forest, and David (1996) further elaborate that machine learning algorithms establish a computational model based on test data, allowing predictions or decisions to be made without explicit programming for the specific task. It is a subset of Artificial Intelligence that functions on the premise that systems can glean insights from data, identify patterns, and autonomously make decisions with limited human involvement. This allows software to interpret its surroundings and make informed decisions based on the data it processes.

Types of Machine Learning

The three primary categories of machine learning are unsupervised, supervised and reinforcement learning.

Supervised Machine Learning

In supervised learning, the objective is to predict a target or outcome variable (dependent variable) using a set of input features (independent variables). A function is constructed to map these inputs to the desired outputs based on the provided variables. The training process iterates until the model achieves a satisfactory level of accuracy on the training data. Examples of supervised learning algorithms include Regression, Decision Tree, Random Forest, KNN, and Logistic Regression (Abdi, 2016). These algorithms utilize historical data to make predictions about future events.

Unsupervised Machine Learning

Unsupervised learning, sometimes referred to as Hebbian learning or self-organization, involves modeling input probability density without a guiding teacher (Hinton & Sejnowski, 1999). A key aspect of unsupervised learning is statistical density estimation, but it also encompasses various other techniques for summarizing and interpreting data characteristics. These algorithms identify and learn patterns within an unlabeled dataset.

Reinforcement Machine Learning

Reinforcement learning involves training machines to make specific decisions by exposing them to environments where they continuously learn through trial and error. Drawing on past experiences, the machine strives to capture the most effective knowledge for making accurate decisions. An illustrative example of reinforcement learning is the Markov Decision Process (Abdi, 2016).

2.5 Deep Learning

Deep learning, a subset of machine learning, utilizes layers of non-linear processing stages to acquire unsupervised features and classify patterns (Deng, 2014). DL is a computer-assisted medical diagnosing approach (Vasilakos et al., 2016). In medical image analysis, DL applications include classification, segmentation, detection, retrieval, and registration of images. DL has emerged as a powerful tool in medical image analysis, revolutionizing the field of breast cancer detection. Deep learning models, specifically convolutional neural networks (CNNs), are capable of automatically learning hierarchical representations of data from large datasets without requiring manual feature extraction. This ability to extract complex features from medical images makes deep learning specifically well-suited for tasks such as tumor detection and classification in breast cancer screening.

2.6 Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) is a deep learning architecture specifically designed for image processing, consisting primarily of two layers: the convolutional layer and the pooling layer. CNNs are a type of feed-forward neural network widely used in artificial intelligence, particularly renowned for their efficacy in image recognition tasks (Nisha, 2021). In CNNs, input data is represented as multidimensional arrays, making them particularly suitable for handling image data. The convolutional layer computes neuron outputs by convolving the input data with shared weights and biases, facilitating the extraction of local features. Following this, the pooling layer reduces the spatial dimensions of the data by subsampling the output from the convolutional layer. However, the extensive training of deep CNNs, which typically involve millions of parameters, necessitates a large number of training images and access to ground truth data, which can be challenging to obtain, particularly in medical applications.

Convolutional Neural Networks (CNNs) have a rich history in image processing and interpretation, especially in medical imaging. In the 1970s, network architectures tailored for image data were regularly developed, showing promise in tasks like handwritten character recognition (Srivastava, 2014). However, it wasn't until the introduction of dropout and rectified linear units, alongside the increased computing power provided by graphical processor units (GPUs), that neural networks became viable for more advanced image recognition tasks. Currently, large-scale CNNs are effectively employed to address complex image recognition challenges spanning various object classes.

2.6.1 Image Processing with Convolutional Neural Network (CNN)

Image processing in Convolutional Neural Networks (CNNs) involves a series of steps where raw image data is transformed and processed to enable accurate image recognition, classification, and segmentation tasks. CNNs excel in image processing tasks because they can autonomously and dynamically acquire spatial hierarchies of features from input images.

Key Steps in Image Processing with CNNs

Input Image Preparation

This is the initial step where images are resized to a fixed dimension to ensure uniformity in the input data, making it easier for the network to process multiple images simultaneously. Pixel values are typically normalized to a range of [0, 1] or [-1, 1], which helps in facilitating faster convergence during training by ensuring that the input values are within a consistent range. This preprocessing step is crucial as it standardizes the input data, enabling the CNN to learn more effectively.

Convolutional Layers

A series of trainable filters, known as kernels, are employed on the input image, generating feature maps that highlight distinctive aspects such as edges, textures, or patterns. These filters are crafted to identify specific visual attributes, enabling the network to grasp diverse elements of the input data across varying abstraction levels. Following the convolution process, an activation function is applied, typically ReLU (Rectified Linear Unit), to introduce non-linearity. This non-linear transformation facilitates the network in discerning intricate patterns and correlations within the data. ReLU works by setting all negative values in the feature maps to zero, which helps in mitigating the vanishing gradient problem and accelerates the convergence of the training process. This combination of convolution and non-linear activation is fundamental in enabling CNNs to automatically and effectively learn and represent the intricate structures and hierarchies present in image data.

Pooling Layers

Pooling layers play a crucial role in Convolutional Neural Networks (CNNs) by effectively reducing the spatial dimensions of feature maps while preserving key information. One widely used pooling technique is max pooling, which operates by selecting the maximum value within a defined window, typically sized 2x2. This process not only streamlines computational complexity but also fosters spatial invariance, enabling the network to recognize features irrespective of their location within the input image. Another type is average pooling, which, unlike max pooling, takes the average value within the window. While average pooling is less commonly used than max pooling, it can be beneficial in scenarios where the average presence of features is more relevant than the presence of a single dominant feature. Both pooling methods contribute to making the model more robust and computationally efficient.

Fully Connected Layers

In Convolutional Neural Network (CNN) architectures, fully connected layers serve a crucial role towards the end of the network, facilitating high-level reasoning and final predictions. Preceding these layers, the feature maps generated by convolutional and pooling layers undergo flattening, converting the multidimensional array of features into a singular vector. This flattening process enables the subsequent fully connected layers, also termed dense layers, to receive the input. Dense layers are characterized by dense connections, where each neuron in one layer is linked to every neuron in the subsequent layer. Within these dense layers, intricate computations occur to integrate the learned features, ultimately leading to the generation of the final output. This design empowers the network to amalgamate the extracted features in a meaningful manner, thereby enabling accurate classifications or predictions.

Output Layer

The output layer in a Convolutional Neural Network (CNN) holds significant importance in generating the final prediction or classification. Particularly in multi-class classification tasks, the softmax function emerges as a commonly employed tool in the output layer. Operating on the raw output scores (logits) obtained from the preceding layer, the softmax function transforms these scores into probabilities, ensuring they collectively sum up to one. Each calculated probability denotes the likelihood of the input image belonging to a specific class within the classification task. This conversion renders the output interpretable, thereby enabling the model to furnish a probabilistic prediction for each class under consideration. Subsequently, the class associated with the highest probability is typically designated as the predicted label, underscoring the efficacy of the softmax function in facilitating classification tasks within deep learning models.

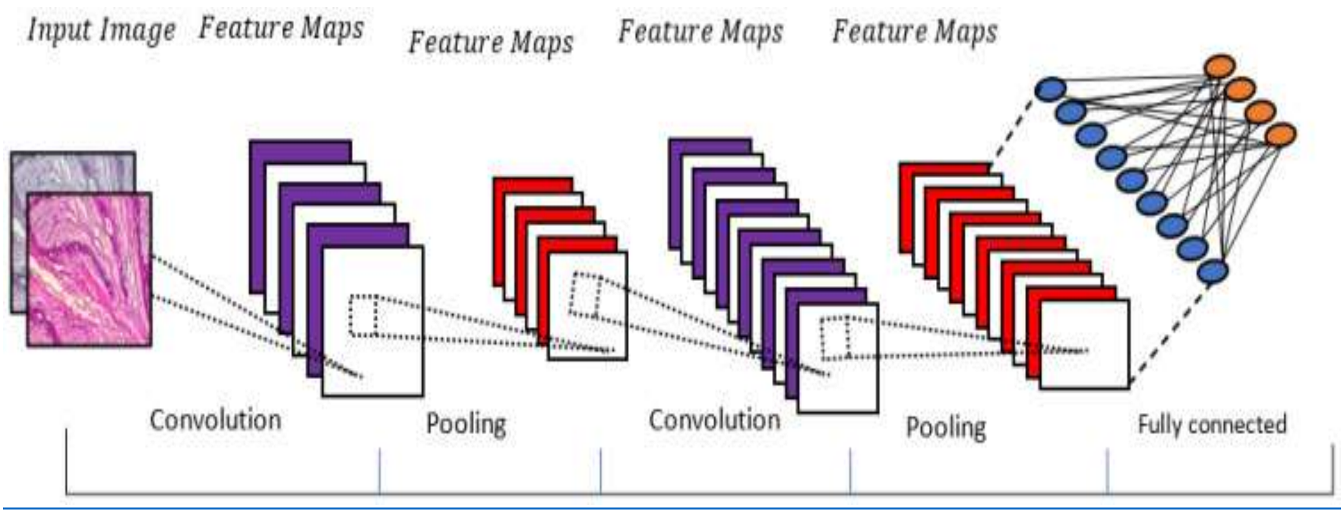

Figure 2: An illustration of the CNN Model

2.7 Convolutional Neural Network Models

ImageNet:

(Deng et al., 2020) ImageNet is a large-scale image dataset that has been instrumental in the progression of computer vision research. It comprises of millions of labeled images across thousands of categories. ImageNet has been widely used as a benchmark dataset for training and evaluating CNN models for image classification and object recognition tasks.

EfficientNet:

In their study titled "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," researchers Mingxing Tan and Quoc V. Le from Google Research, Brain team introduced the EfficientNet model. This research was presented at the 2019 International Conference on Machine Learning. Through their investigation into model scaling, they identified that a balanced adjustment of the network's depth, width, and resolution could enhance its performance. To address this, they proposed a novel scaling strategy, which uniformly scales the depth, width, and resolution of the network. Utilizing neural architecture search, they developed a new baseline network and scaled it up to create the EfficientNets family of deep learning models. These models have demonstrated superior accuracy and efficiency compared to earlier Convolutional Neural Networks (Tan and Le, 2020).

AlexNet:

AlexNet is a groundbreaking CNN architecture credited with catalyzing the widespread adoption of deep learning for image classification tasks (Krizhevsky, Sutskever, and Hinton 2018). Notable components of AlexNet include its incorporation of convolutional layers, max pooling, ReLU activation, and dropout regularization. Structurally, AlexNet comprises five convolutional layers succeeded by three fully connected layers.

GoogLeNet:

GoogLeNet, also known as Inception. It introduced the concept of the Inception module, which performs parallel convolutions at different scales and concatenates their outputs. This module allows the network to capture features at multiple levels of abstraction efficiently. GoogLeNet employs a deep architecture with 22 layers and significantly fewer parameters compared to previous models. It utilizes 1x1 convolutions for dimensionality reduction and incorporates auxiliary classifiers to combat the vanishing gradient problem during training (Szegedy et al., 2015).

2.8 Related Literature

A thorough examination of the literature regarding deep learning-based breast cancer detection reveals a rapidly evolving domain marked by significant advancements in recent years. Researchers have increasingly turned to deep learning techniques, particularly convolutional neural networks (CNNs), to analyze medical imaging data, including mammography, magnetic resonance imaging (MRI), and ultrasound, aiming to enhance early detection and diagnosis of breast cancer.

Numerous studies have concentrated on developing and evaluating deep learning models for breast cancer detection using mammographic images. These models have demonstrated promising outcomes in accurately identifying suspicious lesions and differentiating between benign and malignant tumors (Kooi et al., 2017; Becker et al., 2017). Moreover, researchers have explored the synergy of deep learning with other imaging modalities such as MRI and ultrasound to enhance breast cancer detection and diagnostic accuracy (Yala et al., 2019; Dalmış et al., 2019). For instance, Gupta, Kumar, and Tiwari (2019) proposed a hybrid deep learning model that combines CNNs and recurrent neural networks (RNNs) for breast cancer detection. The model, trained on labeled mammographic images, was evaluated using k-fold cross-validation, with reported sensitivity, specificity, and accuracy metrics. The hybrid model achieved notable performance, with a sensitivity of 94%, specificity of 92%, and accuracy of 93%.

Similarly, Sharma, Singh, and Agarwal (2020) conducted research comparing different deep learning techniques for breast cancer detection, including CNNs, deep belief networks (DBNs), and RNNs. Multiple datasets of mammographic images were employed for training and testing. Through cross-validation, the models' performance metrics, including sensitivity, specificity, and accuracy, were computed. The CNN-based model exhibited commendable performance, achieving a sensitivity of 91%, specificity of 89%, and accuracy of 90%.

Beyond tumor detection, deep learning-based approaches have been applied to other facets of breast cancer diagnosis, encompassing tumor subtype classification, tumor segmentation, and prediction of treatment response. These endeavors have underscored the potential of deep learning models to assist radiologists in interpreting medical images, thereby facilitating more efficient and accurate diagnoses (Cheng et al., 2020; McKinney et al., 2020).

Wang et al. (2022) delved into deep learning-based breast cancer diagnosis and prognosis utilizing multi-omics data. Their study leveraged diverse data modalities, including gene expression profiles, DNA methylation data, and imaging features, to predict breast cancer diagnosis and prognosis. Employing a multi-modal neural network architecture, the model demonstrated robust performance across various tasks, achieving high accuracy, sensitivity, specificity, and AUC-ROC values for tumor subtype classification, tumor segmentation, and treatment response prediction.

Additionally, Ciresan et al. (2013) proposed a deep learning approach for classifying breast cancer histopathology images into benign and malignant categories. Leveraging a deep CNN architecture termed "convolutional neural network (CNN) committee," their model showcased superior accuracy in distinguishing between benign and malignant histopathology images, underscoring the efficacy of deep learning techniques in automated cancer classification tasks.

Venkatesh et al. (2023) explored the prediction of lung cancer using patch processing and deep learning on Computed Tomography (CT) images. Employing a CNN classifier, their model achieved remarkable accuracy, sensitivity, and specificity in discerning between malignant, benign, and normal tumors in CT scans.

Furthermore, Chen, Zhang, and Zhu (2021) investigated deep learning-based breast cancer diagnosis and classification through transfer learning. Fine-tuning pre-trained deep learning models like VGG-16 and ResNet on mammographic images yielded impressive sensitivity, specificity, and accuracy metrics.

These studies collectively highlight the transformative potential of deep learning in breast cancer detection, diagnosis, and prognosis prediction, fostering advancements towards personalized treatment strategies and improved patient outcomes.

2.8.1 Performance Comparison of The Reviewed Classification Models

Table 1:Performance comparison of the reviewed classification models

Author	**Title**	**DL Method**	**Results**
Gupta et al., (2019)	Hybrid Deep Learning Model for Breast Cancer Detection Using Mammographic Images	Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN)	Accuracy-93% Sensitivity-94% Specificity-92% Area Under Curve-0.93
Sharma et al., (2020)	Breast Cancer Detection Using Deep Learning Techniques: A Comparative Study	Convolutional Neural Network (CNN), Deep Belief Networks (DBN) and Recurrent Neural Network (RNN)	Accuracy-90% Sensitivity-91% Specificity-89%
Wang et al., (2022)	Deep Learning-Based Breast Cancer Diagnosis and Prognosis Using Multi-omics Data	Multi-modal Neural Network	Accuracy-92% Sensitivity-90% Specificity-93%

Ciresan et al., (2013)	Deep Learning-Based Classification of Breast Cancer Histopathology Images	Convolutional Neural Network (CNN)	Accuracy-94% Sensitivity-90% Specificity-85% Area Under Curve-0.95
Venkatesh et al., (2023)	A hybrid model for lung cancer prediction using patch processing and deep learning on CT images	Convolutional Neural Network (CNN)	Accuracy-99.96% Sensitivity-98.38% Specificity-59.4%
Chen et al., (2021)	Deep Learning-Based Breast Cancer Diagnosis and Classification Using Transfer Learning	Transfer learning (VGG-16 and ResNet)	Accuracy-94% Sensitivity-95% Specificity-93%

2.9 Research Gap

Despite the promising results, challenges remain in the development and deployment of deep learning models for breast cancer detection. Issues such as data scarcity, model interpretability, and generalizability across diverse populations need to be addressed to ensure the robustness and reliability of deep learning-based systems in clinical practice. Furthermore, efforts are needed to integrate these models into existing healthcare workflows and evaluate their impact on patient outcomes and healthcare delivery. While the existing studies have demonstrated the effectiveness of deep learning models in accurately identifying breast cancer in different imaging modalities, there is a need for further investigation into the generalizability and robustness of these models across diverse patient populations and imaging settings. Many of the existing studies have focused on relatively small datasets or specific patient cohorts, restricting the suitability of the proposed models in real-world clinical practice. Therefore, there is a research gap in exploring the performance and reliability of deep learning algorithms for breast cancer detection in larger, more diverse datasets, considering factors such as variations in imaging protocols, patient demographics, and lesion characteristics. Additionally, breast cancer in Zimbabwe presents its own set of challenges, including limited access to healthcare, lack of awareness and education, limited availability of data, and socioeconomic factors. Addressing these issues within the research gap can contribute to the development of more robust and clinically applicable deep learning models for breast cancer detection using MRI images, specifically tailored to the Zimbabwean context. By considering the unique challenges faced in Zimbabwe, such as limited healthcare access and resources, low awareness, and socioeconomic disparities, researchers can develop targeted approaches that overcome these barriers and contribute to improved breast cancer outcomes in the country.

2.10 The Proposed Approach/Current Study

After observing this the author have decided to focus on utilizing MRI images, leveraging a large dataset, and tailoring the deep learning model for breast cancer diagnosis in the Zimbabwean context is strategically aligned with the identified research gap. By addressing challenges such as data scarcity, model interpretability, and generalizability across diverse populations, this approach aims to overcome limitations highlighted in existing literature. Utilizing MRI images offers several advantages, including high sensitivity, MRI is highly sensitive to changes in tissue composition, allowing it to detect small abnormalities that may be missed by alternative imaging techniques such as mammography or ultrasound, the ability to capture detailed anatomical information and potential improvements in diagnostic accuracy compared to other imaging modalities. Also, MRI is advised as a screening tool for women with a heightened risk of breast cancer, such as those with a family history of the disease or carriers of BRCA gene mutations, due to its high sensitivity in detecting early-stage tumors. Employing a large dataset allows for robust model training and validation, improving reliability and generalizability. Tailoring the model to Zimbabwean challenges, including limited healthcare access and socioeconomic disparities, aims to bridge the gap between research and clinical practice, ultimately improving breast cancer outcomes in the country. This comprehensive strategy contributes significantly to advancing breast cancer detection and management in Zimbabwe and serves as a potential model for similar healthcare settings worldwide.

2.11 Conclusion

The researcher effectively acquired and compiled relevant information and data relevant to the research topic. Various concepts were drawn from academic papers, textbooks, and online sources, uncovering gaps that require further exploration. The insights gleaned from these diverse sources will be integrated into subsequent chapters of the study to fulfill the research project's objectives. The subsequent chapter will explore into the methodology employed in designing and developing the proposed solution.

CHAPTER 3

METHODOLOGY

3.0 Introduction

Research involves investigating a specific issue of interest through scientific inquiry or detailed analysis. Depending on whether the research is exploratory, descriptive, or diagnostic, quantitative or qualitative approaches may be utilized. This chapter details the methodology employed in a research study on deep learning-based breast cancer detection using MRI images. It outlines the systematic approach adopted to achieve the research objectives, ensuring rigor and reliability in the investigation process. Building on the information collected in the previous section, the researcher will determine the necessary steps to develop a solution and select the most effective approach from various strategies to accomplish the study's objectives. The section primarily emphasized the methodology, data collection methods, research design, and criteria (functional and non-functional) and based on that it provides a comprehensive understanding of how the study was conducted. The chapter proceeds to explore the solution provided that is, implementation of the model, the structure of the dataset and how the dataset was acquired, image pre-processing, training and saving the model.

3.1 Research Design

Moule and Goodman (2013) argue that the foundation of a study is laid through its research design. According to (Polit and Hungler, 2014), research design refers to the plan or framework employed by researchers to tackle research questions and navigate potential challenges that may arise during the research process. Researchers have the option to choose from four research models: observational, experimental, simulation, or generated. In this particular study, the researcher decided to adopt experimental methods due to the need for continuous development and testing to achieve the desired outcomes. The experimental approach was preferred as it involves conducting trials or preliminary investigations. By actively intervening, the researcher collected experimental data by manipulating a variable to observe and measure the resulting changes or establish differences.

3.2 Requirement Analysis

In the process of requirement analysis for the breast cancer detection system using deep learning, meticulous documentation of both functional and non-functional specifications is paramount. This involves structuring incoming data, assessing its relevance, and considering potential constraints, like dataset availability and processing power during machine training, that might influence the design process. It is crucial to ensure that the identified requirements are practical, documented, tested, actionable, traceable, and measurable, aligning closely with identified business needs. Additionally, the acquired requirements undergo thorough review and revision to ensure uniformity and clarity. Any constraints, particularly those related to data availability, are carefully taken into account to develop a comprehensive and actionable specification that addresses the needs of healthcare specialists effectively. This rigorous approach to requirement analysis lays the foundation for the successful design and development of the breast cancer detection system, ensuring that it meets the specific demands of the healthcare domain.

3.2.1 Functional Requirements

Functional requirements denote the precise tasks and functionalities essential for the system to accomplish its intended goals. In the context of the breast cancer detection system using deep learning these requirements outline the actions and behaviors that the system should exhibit when detecting and diagnosing breast cancer from MRI images. According to Abram et al. (2004), functional requirements are crucial as they define the core functionalities of the system and serve as a blueprint for system development. Therefore, the functional requirements for the breast cancer detection system using deep learning should encompass key tasks such as image preprocessing, feature extraction, lesion segmentation, and classification. The suggested system must be capable of meeting the following criteria:

- The system should be able to preprocess MRI images to enhance their quality and remove noise, artifacts, and irrelevant information.
- The system should be able to extract relevant features from preprocessed MRI images to capture distinctive patterns indicative of breast cancer.
- The system should provide functionality for prediction of breast cancer based on the extracted features from MRI images.

3.3.2 Non-Functional Requirements

Non-functional requirements refer to the criteria that describe how the system should perform, rather than the specific functions it should execute. These requirements typically encompass aspects such as performance, reliability, usability, scalability, security, and maintainability. For instance, performance requirements specify the system's responsiveness and processing speed, ensuring timely analysis of medical images. Reliability requirements dictate the system's ability to accurately detect cancerous lesions across diverse datasets and patient populations. Usability requirements focus on the user interface design, ensuring that healthcare professionals can easily interpret and interact with the system. Scalability requirements address the system's ability to handle an increasing volume of medical data as the dataset grows. Security requirements encompass measures to protect patient data privacy and prevent unauthorized access. Finally, maintainability requirements dictate the ease with which the system can be updated, maintained, and enhanced over time (Babar et al., 2012). The suggested system should be capable of meeting the following requirements:

- The system should be reliable and accurate in detecting breast cancer lesions from MRI images.
- The system should be able to provide a user-friendly interface for seamless uploading, viewing, and interpretation of MRI images by healthcare professionals.
- The system should be able to generate comprehensive diagnostic reports containing lesion characteristics, tumor size, and malignancy probability to aid in treatment planning and patient management.
- The system should be scalable to accommodate varying workloads and increasing MRI image volumes without compromising performance or reliability.
- The system must be accessible at all times.
- The system should be quickly recoverable to operational status in case of failure.

3.3.3 Software Requirements

- Windows 10/11 operating system
- Streamlit library
- Tensorflow
- Python 3.9
- Google Chrome Browser
- SPYDER (Scientific Python Development Environment)

- Apache or Tomcat Server
- Keras
- Anaconda Python IDE
- Jupyter Notebook

3.3.4 Hardware Requirements

- Keyboard
- Monitor
- Core i5 CPU
- Mouse

3.4 System Development

This section presents a summary of the system development process and outlines the software tools and models utilized to achieve the desired results. It details the steps taken to develop a functional model and obtain accurate results, highlighting the software tools and models incorporated throughout the development process.

3.5 System Development Tools

During the system development process, different tools are vital for implementing, training, and evaluating deep learning models for breast cancer diagnosis. In this section, the author had to determine a suitable methodology for developing the proposed solution. However, the author identified numerous frameworks for different projects, each with its own merits and demerits depending on the system's design and its ability to produce accurate results aligned with the set objectives. The author chose the Agile methodology as a technique for the proposed solution because in the realm of system development methodologies, Agile methodology stands out as a highly effective approach for projects involving iterative development and continuous improvement. Agile methodology emphasizes collaboration, adaptability, and customer feedback, which are particularly beneficial in research projects like breast cancer detection using deep learning. By decomposing the development process into small, manageable tasks or iterations, Agile allows for frequent reviews and adjustments based on evolving requirements and insights gained from ongoing experimentation. This iterative approach promotes flexibility and responsiveness to changing priorities, enabling researchers to refine their methods and models iteratively. Additionally, Agile fosters close collaboration between multidisciplinary teams, including researchers, developers, and healthcare professionals, facilitating effective communication and knowledge sharing.

3.5.1 Agile Model

The Agile model represents an iterative and incremental approach to software development, focusing on flexibility, collaboration, and customer feedback throughout the development process (Sutherland et al., 2009). Rooted in the Agile Manifesto, this methodology prioritizes individuals and interactions, working software, customer collaboration, and responding to change, valuing these over rigid processes and extensive documentation (Beck et al., 2001). Within the Agile model, development tasks are divided into small, manageable units called iterations or sprints, typically lasting between one to four weeks. Throughout each iteration, cross-functional teams collaborate to deliver a potentially shippable product increment (Schwaber & Sutherland, 2017). Continuous communication and collaboration among team members, stakeholders, and customers are integral components of the Agile methodology. This ongoing interaction facilitates regular feedback and adjustments, ensuring the product aligns with the evolving needs and expectations of stakeholders (Cockburn & Highsmith, 2001). At the beginning of each iteration, the team collaboratively defines the requirements and priorities for the upcoming work. These requirements are captured in the form of user stories or tasks, which are then estimated and added to the iteration backlog (Cohn, 2005). During the iteration, the team focuses on implementing and testing prioritized user stories, aiming to deliver functional software that offers real value to the customer (Larman & Vodde, 2009). At the iteration's conclusion, the team holds a review meeting to showcase the completed work to stakeholders and gather their feedback. This feedback is then used to plan the next iteration, ensuring continuous improvement and value delivery (Schwaber & Beedle, 2001). The Agile model as a whole provides a flexible and adaptive approach to software development, enabling teams to quickly respond to changing requirements and deliver high-quality software that meets customer needs.

The Agile Model encompasses several phases:

Planning: In this phase, the team collaborates to define the project's scope, establish key objectives, and prioritize features or user stories for development. This involves creating a product backlog, a prioritized list of tasks or user stories to be completed during the project.

Iteration/Sprint Planning: Agile projects are segmented into iterations or sprints, typically lasting between one to four weeks. At the onset of each iteration, the team conducts sprint planning meetings to choose tasks from the product backlog to work on during the sprint. These tasks are further broken down into user stories, estimated, and assigned to team members.

Development: During the development phase, the team works collectively to implement the selected user stories. This encompasses coding, testing, and integrating features into the product increment. Development tasks are usually completed in short, time-boxed cycles to ensure rapid progress and regular feedback.

Daily Stand-up Meetings: Throughout the iteration, the team holds daily stand-up meetings, or daily scrums, to provide updates on progress, discuss any obstacles, and ensure alignment towards achieving sprint goals.

Review and Demo: At the conclusion of each iteration, a sprint review meeting is conducted to showcase completed work to stakeholders and gather feedback. This entails demonstrating the product increment and discussing any necessary changes based on stakeholder input.

Retrospective: Following the sprint review, a retrospective meeting is held to reflect on the sprint process and identify areas for improvement. This involves discussing successes, areas for enhancement, and actions to be taken to enhance future iterations.

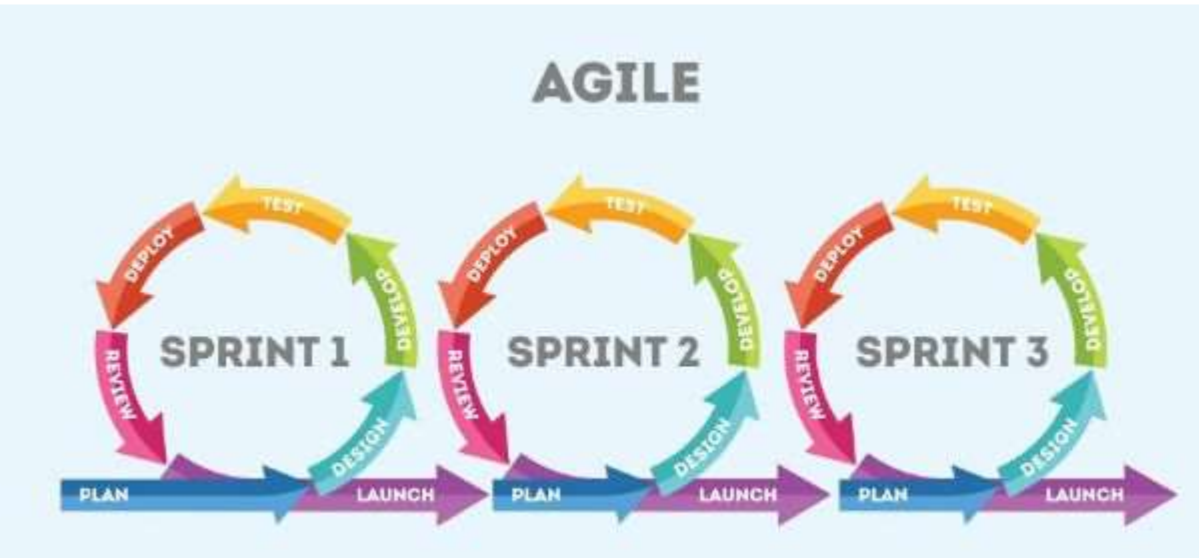

Figure 3: Agile Model

The system was built using a few key tools:

1. **Python**: This programming language was used to create the system. It helped in developing a model to determine if a patient has breast cancer. Its Artificial intelligence frameworks have simplified the creation of the model for prediction.
2. **Keras:** This is a software library that works with Python and is used for building artificial neural networks. It makes it easier to experiment with deep neural networks and is designed to be user-friendly.
3. **Anaconda Python IDE:** Anaconda is a distribution of Python and R languages specifically tailored for scientific computing. It simplifies package management and deployment, making it suitable for various operating systems.

3.6 Summary of how the system works

A deep learning-based breast cancer detection system using MRI images employs advanced neural network architectures to analyze medical images and identify potential signs of breast cancer. The process typically begins with the collection of MRI images from patients, which are then pre-processed to enhance image quality and remove any artifacts. These pre-processed images are fed into a deep learning model trained on a large dataset of labeled MRI scans, where the model learns to automatically extract relevant features indicative of breast cancer lesions. Through numerous layers of interconnected neurons, the deep learning model can identify patterns and abnormalities within the images that may signify the presence of tumors or suspicious regions. During inference, the trained model takes in new MRI images and generates predictions regarding the likelihood of cancerous lesions, providing valuable insights to healthcare professionals for diagnosis and treatment planning. By leveraging the power of deep learning, this system offers a non-invasive and efficient approach to breast cancer detection, potentially aiding in early diagnosis and improving patient outcomes.

3.7 System Design

Reviewing the requirements specification document provides clarity on how the system's components and data align with the specified requirements. This phase illustrates the system's organization and consistency as it advances to the subsequent stage.

3.7.1 Dataflow Diagrams

A Data Flow Diagram (DFD) illustrates how information moves within a system using symbols such as rectangles, circles, and arrows. It shows how inputs connect to outputs until the end of the system. The labels on data flow in a DFD describe the type of data involved. DFDs offer valuable insights into how information changes within a system and how the final output is shown.

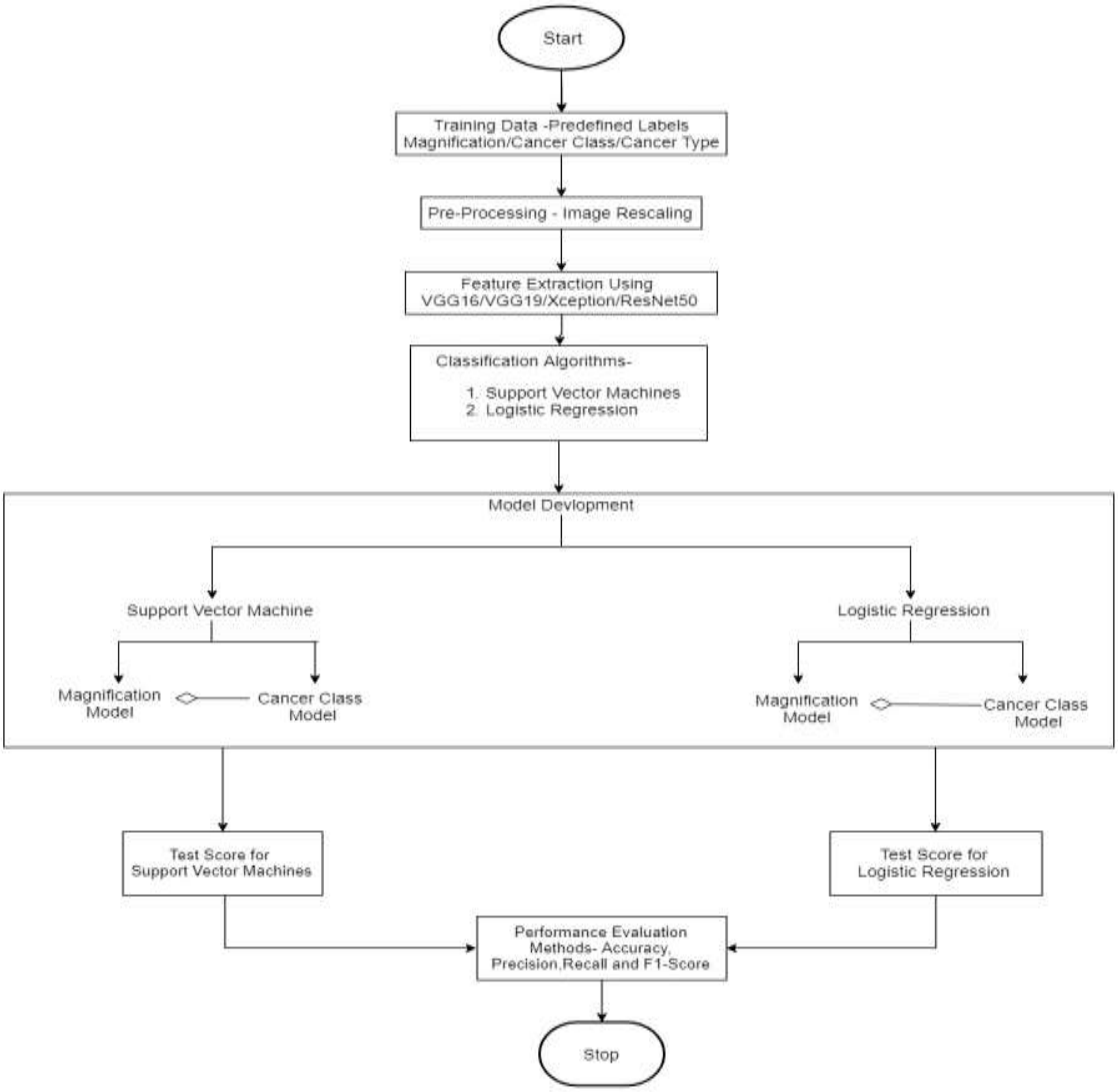

Figure 4:Dataflow Diagram

3.7.2 Proposed System Flow Chart

A flow chart visually depicts the workflow or process of system development. It demonstrates the system's functioning and outlines every decision made by the system during the entire process. Essentially, it acts as a diagrammatic representation of an algorithm, furnishing a step-by-step guide. The system under investigation comprises the following flow chart.

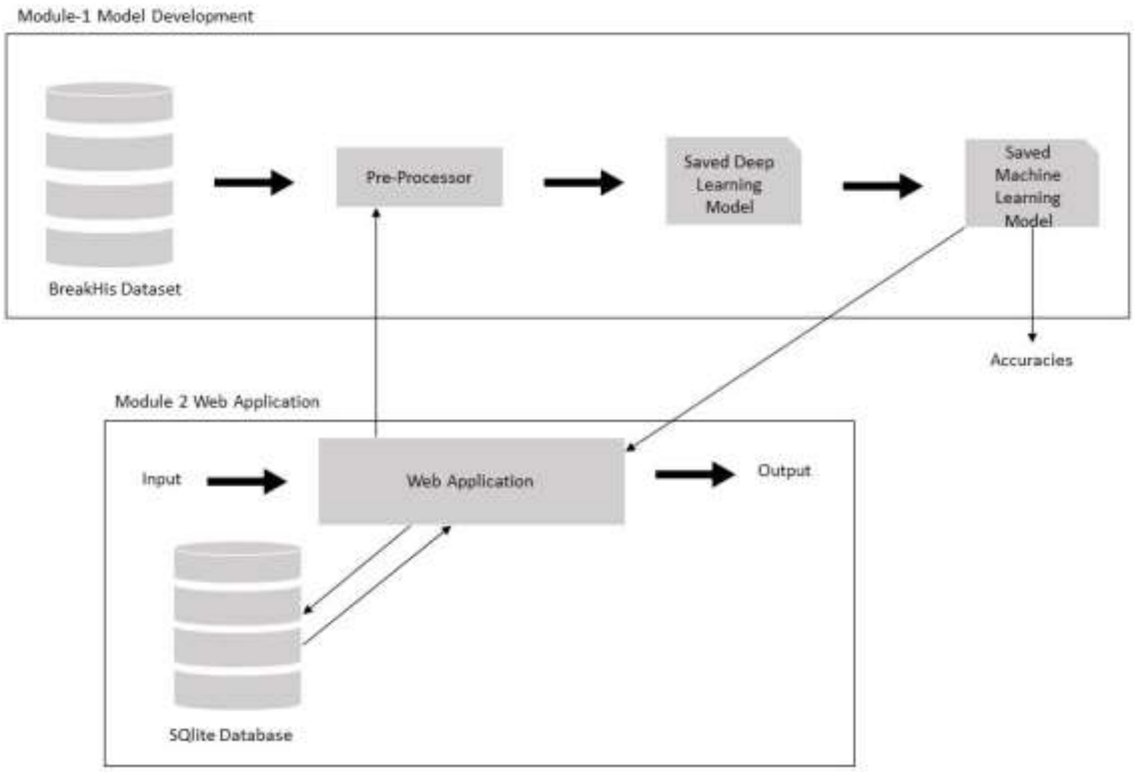

Figure 5: System Flow Chart

3.8 Dataset

The BreakHis dataset comprises 9,109 microscopic images capturing breast tumor tissue from 82 patients. These images vary in magnification levels, including 40X, 100X, 200X, and 400X, and encompass 2,480 benign and 5,429 malignant samples. Each image is formatted as 700x460 pixels, featuring 3-channel RGB and 8-bit depth in each channel, and saved in PNG format.

This dataset categorizes samples into two primary groups: benign tumors and malignant tumors. Benign tumors, characterized as non-cancerous, typically exhibit slow growth without metastasis. Conversely, malignant tumors, which are cancerous, possess the capability to invade adjacent tissues and metastasize to distant sites, posing severe health risks.

The samples in the BreakHis dataset were collected using the SOB (Scarborough, Ontario, and Buffalo) method, also known as partial mastectomy or excisional biopsy. This method entails the removal of a larger tissue sample under general anesthesia in a hospital setting.

Magnification	Benign	Malignant	Total
40X	652	1,370	1,995
100X	644	1,437	2,081
200X	623	1,390	2,013
400X	588	1,232	1,820
Total of Images	2,480	5,429	7,909

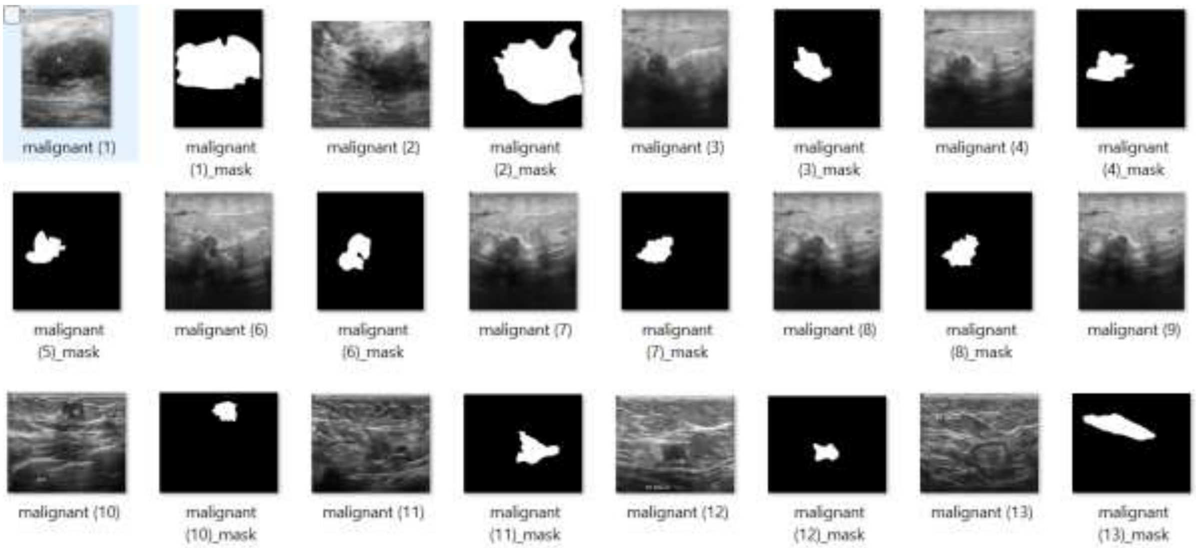

Figure 6:Snapshot of the Dataset

3.9 Solution

This section shows the solution model, how it predicts the results using the algorithms of deep learning. To come up with a functional solution that would solve the research problem, the researcher made analysis the algorithm to determine the error rate and accuracy rate so as to get more accurate results in prediction.

3.9.1 Image Processing

3.9.1.1 Resize Image

When defining the model's architecture, one requirement is to establish a fixed input format. It is essential to remember that there is a trade-off between computational speed and information loss. Specifically, reducing the size of an image removes information (pixels). While less information results in faster training times, it can also lead to decreased overall accuracy.

3.9.1.2 Image Cropping

The cropping of the MRI images will be done to remove the background and unwanted region.

3.9.1.3 Gaussian Blur

Images, like other signals, can be susceptible to various types of noise, often originating from the source, such as the camera sensor. Image smoothing techniques are employed to mitigate noise effects. In OpenCV, image smoothing, also known as blurring, can be achieved through various methods. Gaussian filters, for instance, possess characteristics beneficial for noise reduction, such as minimal overshoot and reduced rise and fall times. These filters effectively smooth sharp edges in images while minimizing excessive blurring. In Gaussian blur, a Gaussian kernel replaces the traditional box filter, with parameters specifying the kernel's width, height, and standard deviations (sigmaX and sigmaY) in the X and Y directions, respectively. Gaussian blur is particularly adept at removing Gaussian noise from images.

A crucial preprocessing step involved mitigating lighting effects by applying masks to the image and resizing it to dimensions of 224×224. Subsequently, Gaussian blur was applied to enhance image quality. Uninformative regions were cropped out, retaining only essential parts of the image. To generate a mask, the MRI image underwent grayscale conversion, with a tolerance threshold set above 7. This step aimed to eliminate black areas from the image, preserving informative content. After cropping and resizing the image to match the model's requirements, Gaussian blur was applied for further enhancement. A standard deviation value of 10 was chosen for both the X and Y directions. Utilizing a Gaussian kernel, each point in the input array underwent convolution and summation to produce the output array.

3.9.1.4 Data Augmentation

In machine learning, data augmentation refers to methods that artificially expand a dataset by transforming existing examples, thereby increasing the training data volume. Although the newly generated data points are not independent and identically distributed, data augmentation implicitly regularizes models and enhances generalization, as indicated by statistical learning theory (Vapnik & Chervonenkis, 1971). Data augmentation has been widely utilized in machine learning for an extended period (Simard et al., 1992) and is acknowledged as a crucial element in many models (Ciresan et al., 2010; Krizhevsky et al., 2012; LeCun et al., 2015).

One common challenge in machine learning is handling unbalanced group sizes. During model training, the goal is to improve precision in subsequent iterations (epochs). Since the model learns by identifying patterns to distinguish between groups, underrepresented groups may not be learned as effectively as overrepresented ones due to their infrequent appearance. To mitigate the effects of over- or under-representation, data augmentation is used. This involves adjusting specific parameters and applying random alterations to the original training images. These random alterations are applied in each epoch, ensuring that the model trains on "different" images in every iteration.

3.9.1.5 Dropout Regularization

Dropout is a strategy utilized in the training of neural networks, where randomly chosen neurons are excluded or "dropped out" during each iteration. This implies that their influence on activating downstream neurons is temporarily eliminated during the forward pass, and no weight updates are applied to these neurons during the backward pass. As a neural network learns, neurons' weights settle into their respective roles within the network, often becoming specialized for particular features. However, neighboring neurons may overly depend on this specialization, resulting in a model that is too narrowly tuned to the training data and susceptible to overfitting. This phenomenon, termed complex co-adaptations, can impede the network's capacity to generalize effectively to unseen data. By introducing random dropout of neurons during training, the network becomes less sensitive to the specific weights of individual neurons, leading to enhanced generalization and decreased risk of overfitting.

3.9.2 Training Model

```
# Training the model for 10 epochs with a batch size of 32(i.e. len(X_train)/batch_size)
history = model.fit(datagen.flow(X_train,y_train, batch_size = 32),
                    epochs = 10, validation_data = datagen.flow(X_val, y_val),
                    callbacks = callbacks)

Epoch 1/10
147/147 [==============================] - 26s 177ms/step - loss: 0.1182 - accuracy: 0.9627 - val_loss: 0.1209 - val_accurac
y: 0.9234

Epoch 00001: val_loss improved from inf to 0.12086, saving model to /content/drive/MyDrive/Colab Notebooks/Kaggle_Pneumonia_
Detection(CNN)/model.h5
Epoch 2/10
147/147 [==============================] - 26s 174ms/step - loss: 0.1108 - accuracy: 0.9638 - val_loss: 0.1731 - val_accurac
y: 0.7854

Epoch 00002: val_loss did not improve from 0.12086
Epoch 3/10
147/147 [==============================] - 26s 174ms/step - loss: 0.1064 - accuracy: 0.9668 - val_loss: 0.0284 - val_accurac
y: 0.8065
```

Figure 7:Training the System

3.9.3 Implementation

Figure 8:Model Frontend with Streamlit

3.10 Summary

This chapter mainly discusses the approach used to create and design the system. Various techniques and methods were employed throughout the development process, with a focus on utilizing Python neural network frameworks. The subsequent chapter delves into the discussion and analysis of the results obtained from the implemented solution. Additionally, the following chapter provides a conclusion based on the results obtained.

CHAPTER 4

DATA PRESENTATION, ANALYSIS AND INTERPRETATION

4.1 Introduction

This chapter focuses on the crucial phase of examining and interpreting the outcomes obtained from testing the research model proposed in this study. The main goal is to evaluate the efficacy and accuracy of the model in detecting breast cancer. To accomplish this, a range of performance metrics are utilized, including accuracy, recall, specificity, sensitivity, weighted F1 score, prevalence, and error rate. The central aspect of this analysis relies on the application of the confusion matrix, which offers a comprehensive overview of the classification model's performance. Through thorough testing, incorporating white box testing, black box testing, and unit testing methodologies, the chapter aims to offer a detailed presentation of the model's outcomes. Ultimately, the chapter concludes with a definitive assessment of whether the research objectives have been achieved, based on the performance and insights gleaned from the tested model.

4.2 Software Testing

Software testing is a structured process aimed at evaluating and validating software to ensure it adheres to specified requirements and operates as intended. Its primary objective is to identify defects, errors, or bugs in the software product, thus enhancing its quality and dependability. This process entails running software or system components through manual or automated tools to assess various aspects of interest. Moreover, software testing serves to mitigate the risks associated with deploying faulty software, such as financial losses, damage to reputation, and compromised user satisfaction. Ultimately, comprehensive software testing is crucial for delivering high-quality, dependable software products that align with user expectations and fulfill business objectives. To validate and verify the process, the author performed both black box and white box testing on the research. Subsequently, the test outcomes were compared against the functional and non-functional requirements of the proposed solution.

4.2.1 Black Box Testing

Black box testing is a software testing methodology that assesses the functionality of a software application without requiring knowledge of its internal code structure, design, or implementation specifics. Testers evaluate the software solely based on its external behavior and specifications, treating it as an opaque "black box" with unknown internal workings. This approach enables testers to replicate real-world usage scenarios and interactions with the software, facilitating the identification of defects, errors, or inconsistencies in its functionality or behavior.

Black box testing is instrumental in validating the correctness, comprehensiveness, and usability of software applications from an end-user standpoint, ensuring that they meet user requirements and deliver the intended functionality effectively. Hence, the proposed system underwent testing to evaluate its capability in detecting and categorizing breast cancer based on the provided data following its training. The author performed a black box test on the model and obtained the following results:

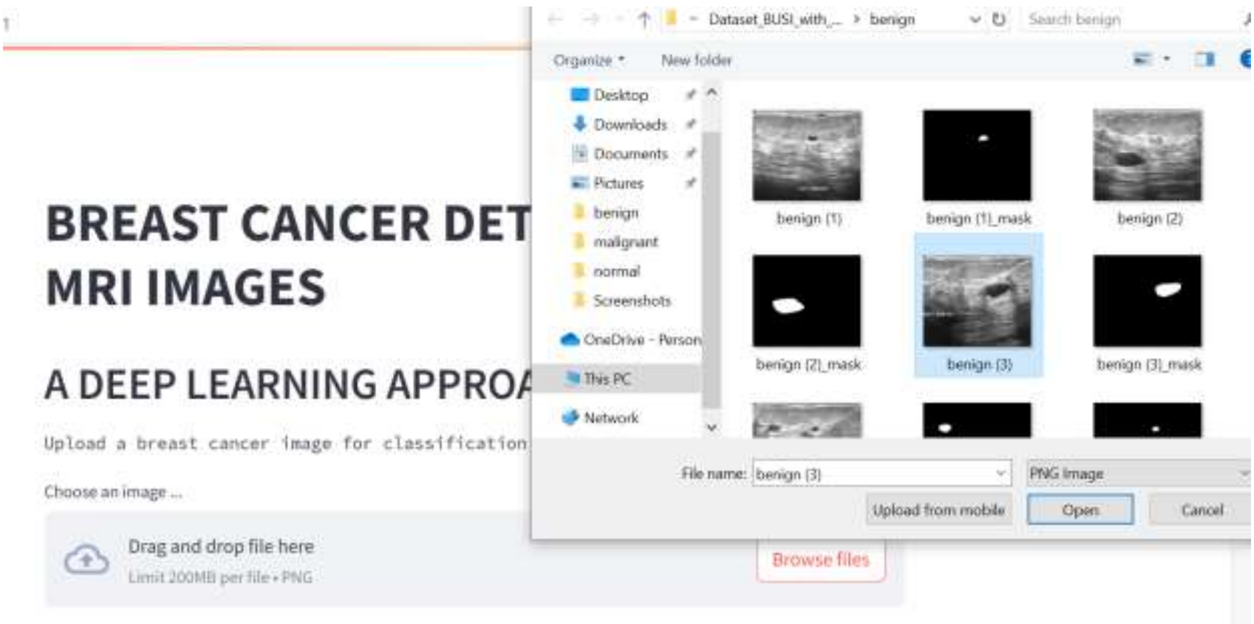

Figure 9:Uploading an image from Computer

Figure 10:An uploaded image that has been classified

Figure 11:Testing the System with wrong File Format

4.2.2 White Box Testing

White box testing is a software testing methodology that involves examining the internal mechanisms and implementation details of a software application. Unlike black box testing, which focuses on assessing software functionality from an external perspective, white box testing delves into the code structure, logic, and program flow to evaluate its accuracy and robustness. Testers analyze the source code, algorithms, control flow, and data flow within the application to create test cases that target specific paths, branches, and conditions.

By comprehending the internal structure of the software, white box testing aims to uncover errors, bugs, and vulnerabilities resulting from programming flaws, logic errors, or insufficient code coverage. White box testing plays a crucial role in validating the reliability, maintainability, and quality of the software codebase, enabling developers to detect and address defects early in the development lifecycle. The developer conducted white box testing on the model, scrutinizing its internal mechanisms and implementation specifics to evaluate its performance. This comprehensive analysis aids in identifying and addressing any potential issues or weaknesses within the software application.

```
# Training the model for 10 epochs with a batch size of 32(i.e. len(X_train)/batch_size)
history = model.fit(datagen.flow(X_train,y_train, batch_size = 32),
                    epochs = 10, validation_data = datagen.flow(X_val, y_val),
                    callbacks = callbacks)

Epoch 1/10
147/147 [==============================] - 26s 177ms/step - loss: 0.1182 - accuracy: 0.9627 - val_loss: 0.1209 - val_accurac
y: 0.9234

Epoch 00001: val_loss improved from inf to 0.12086, saving model to /content/drive/MyDrive/Colab Notebooks/Kaggle_Pneumonia_
Detection(CNN)/model.h5
Epoch 2/10
147/147 [==============================] - 26s 174ms/step - loss: 0.1108 - accuracy: 0.9638 - val_loss: 0.1731 - val_accurac
y: 0.7854

Epoch 00002: val_loss did not improve from 0.12086
Epoch 3/10
147/147 [==============================] - 26s 174ms/step - loss: 0.1064 - accuracy: 0.9668 - val_loss: 0.0284 - val_accurac
y: 0.8065
```

Figure 12: Testing the System for loss and accuracy

```
In [55]: # Predict the label of the test_images
pred = model.predict(test_images)
pred = np.argmax(pred,axis=1)

# Map the label
labels = (train_images.class_indices)
labels = dict((v,k) for k,v in labels.items())
pred = [labels[k] for k in pred]

# Display the result
print(f'The first 5 predictions: {pred[:5]}')

5/5 [==============================] - 9s 1s/step
The first 5 predictions: ['benign', 'benign', 'malignant', 'benign', 'benign']
```

Figure 13: Testing the System to predict the labels of test images

4.3 Evaluation Measures and Results

4.3.1 Confusion Matrix

Once data cleaning, preprocessing, and wrangling are completed, the next step involves feeding the data into a sophisticated model, which produces output probabilities. However, assessing the effectiveness of our model presents a challenge. Improved effectiveness corresponds to enhanced performance, aligning with our objectives. This is where the confusion matrix becomes indispensable. A confusion matrix is a tabular representation commonly used to assess the performance of a classification model on a set of test data with known true values. Relying solely on classification accuracy may not offer a comprehensive evaluation, especially when dealing with imbalanced class distributions or multi-class datasets. By employing a confusion matrix, we can delve deeper into the evaluation of a classification model's performance, highlighting both correct classifications and types of misclassifications. Below, you'll find the normalized confusion matrix for the model.

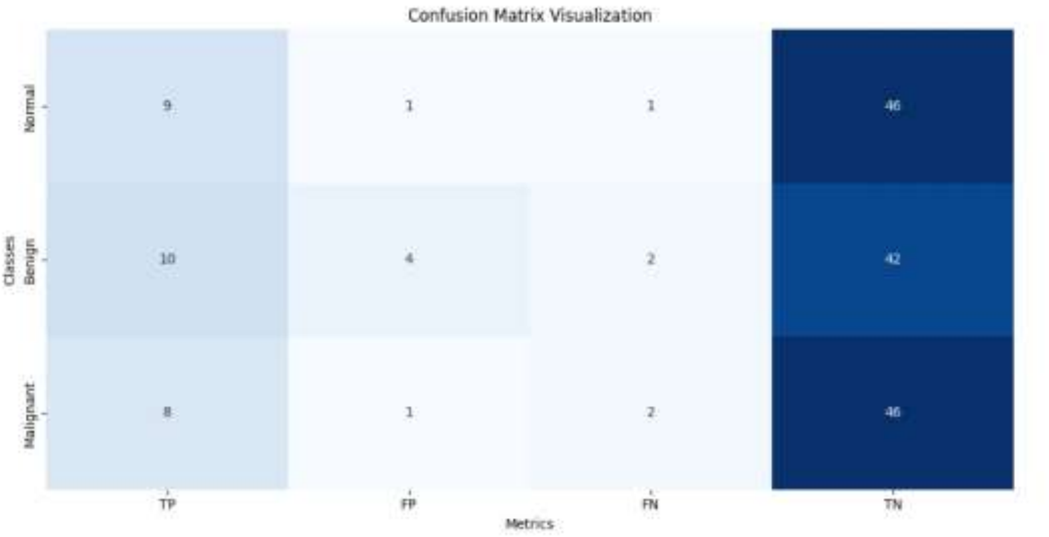

Figure 14:Confusion Matrix

4.3.1.1 Metrics of The Confusion Matrix

True Positive (TP):

- This metric denotes the number of predictions where the model accurately predicts the positive outcome as positive.

True Negative (TN):

- TN represents the count of predictions where the model correctly predicts the negative outcome as negative.

False Positive (FP):

- FP indicates the number of predictions where the model inaccurately predicts the negative outcome as positive.
- Also referred to as a "Type I error."

False Negative (FN):

- FN signifies the number of predictions where the model inaccurately predicts the positive outcome as negative.
- Also termed a "Type II error."

Table 2: Confusion Matrix values/Metrics

	TP	**FP**	**FN**	**TN**
Benign	10	4	2	42
Malignant	8	1	2	46
Normal	9	1	1	46

The table 2 above shows the true positive(TP), false positives(FP), false negatives(FN) and true negatives(TN) for each class.

4.4 System Accuracy, Sensitivity, Specificity, Weighted F1 Score, Error Rate and Precision

Accuracy

- It gives the number of correct predictions to the total number of predictions. It gives the overall accuracy of the model.
- It is given by the formular (number of correct predictions / total number of predictions)
- **Accuracy = (TP + TN) / (TP + TN + FP + FN)**

Table 3:Accuracy for all classes

Classes	**Accuracy**
Benign	Accuracy = (TP+TN)/(TP+TN+FP+FN) = (10 + 42) / (10 + 4 + 2 + 42) =52/58 =0.89655 =**89.7%**
Malignant	Accuracy = (TP+TN)/(TP+TN+FP+FN) = (8 + 46) / (8 + 46 + 2 + 1) =54/57 =0.94736

	=**94.7%**
Normal	Accuracy = (TP+TN)/(TP+TN+FP+FN) = (9 + 46) / (9 + 1 + 1 + 46) =55/57 =0.96491 =**96.5%**

Average Accuracy = accuracy of all 3 classes / 3

= (0.89655 + 0.94736 + 0.96491) / 3

= 93.6%

Misclassification Rate/ Error Rate

- The error rate quantifies the proportion of incorrect made by a model out of the total number of predictions. It provides an overall measure of how often the model makes mistakes
- **Error rate = (FP + FN) / (TP + TN + FP + FN) or (1 - Accuracy)**

Table 4:Error Rate for all classes

Classes	**Error Rate**
Benign	Error rate = (FP+FN)/(TP+TN+FP+FN) = (4 + 2) / (10 + 4 + 2 + 42) =6/58 =0.1034 =**10.3%**
Malignant	Accuracy = (FP+FN)/(TP+TN+FP+FN) = (1 + 2) / (8 + 46 + 2 + 1) =3/57 =0.0526 =**5.3%**
Normal	Accuracy = (FP+FN)/(TP+TN+FP+FN) = (1 + 1) / (9 + 1 + 1 + 46)

	=2/57 =0.03508 =**3.5%**

Average Error Rate = Error rate of all 3 classes / 3

= (0.1034 + 0.0526 + 0.03508) / 3

= 0.0636

=6.4%

Sensitivity/Recall/True Positive Rate

- It indicates the proportion of actual positive instances that are correctly identified by the model.
- **Recall = TP / (TP + FN)**

Table 5:Recall for all classes

Classes	**Recall**
Benign	Recall = TP/(TP+FN) = (10) / (10 + 2) =10/12 = 0.8333 = **83.3%**
Malignant	Recall = (TP)/(TP+FN) = 8 / (8 + 2) =8/10 =0.8 =**80%**
Normal	Recall = TP/(TP+FN) = 9 / (9 + 1) =9/10 =0.9 =**90%**

Average Recall = Recall of all 3 classes / 3

= (0.833 + 0.8 + 0.9) / 3

= 0.8444

= 84.4%

Specificity/True Negative Rate

- It indicates the proportion of actual negative instances that are correctly identified by the model as negative.
- **Specificity = TN / (TN + FP) or 1-FP rate**
- Equivalent to 1 minus False Positive Rate

Table 6:Specificity for all classes

Classes	**Specificity**
Benign	Specificity = TN/(TN+FP) = 42 / (42 + 4) =42 / 46 =0.9130 =**91.3%**
Malignant	Specificity = TN/(TN+FP) = 46 / (46 + 1) =46 / 47 =0.9787 =**97.9%**
Normal	Specificity = TN/(TN+FP) = 46 / (46 + 1) =46 / 57 =0.9787 =**97.9%**

Average Specificity = Specificity of all 3 classes / 3

= (0.9130 + 0.9787 + 0.9787) / 3

=0.9568

=**95.7%**

Precision

- When it predicts yes, how often is it correct?
- **Precision=TP / (TP + FP)**

Table 7:Precision for all classes

Classes	Precision
Benign	Precision = TP/(TP+FP) = 10 / (10 + 4) =0.7143 =**71.4%**
Malignant	Precision = TP/(TP+FP) = 8 / (8+1) =0.8888 =**88.9%**
Normal	Precision = TP/(TP+FP) = 9 / (9 + 1) =0.9 =**90%**

Average Precision = Precision of all 3 classes / 3

= (0.7143 + 0.8888 + 0.9) / 3

= 83.4%

F1-Score/F1 Measure

- It is the weighted mean of precision and recall, providing a balance between the two metrics.
- **F1-score = 2 x (Precision x Recall / Precision + Recall)**

= 2TP / (2TP + FP + FN)

Table 8:F1-score for classes

Classes	F1-score

Benign	F1-score = 2 x (Precision x Recall / Precision + Recall) = 2 x (0.7143*0.833 / 0.7143 + 0.833) = 0.7692 = **76.9%**
Malignant	F1-score = 2 x (Precision x Recall / Precision + Recall) = 2 x (0.888*0.8 / 0.888 + 0.8) = 0.8420 = **84.2%**
Normal	F1-score = 2 x (Precision x Recall / Precision + Recall) = 2 x (0.9*0.9 / 0.9 + 0.9) = 0.9 = **90%**

Average F1-score = F1-score of all 3 classes / 3

= (0.7692 + 0.8420 + 0.9) / 3

= 83.7%

4.5 Training & Validation Loss

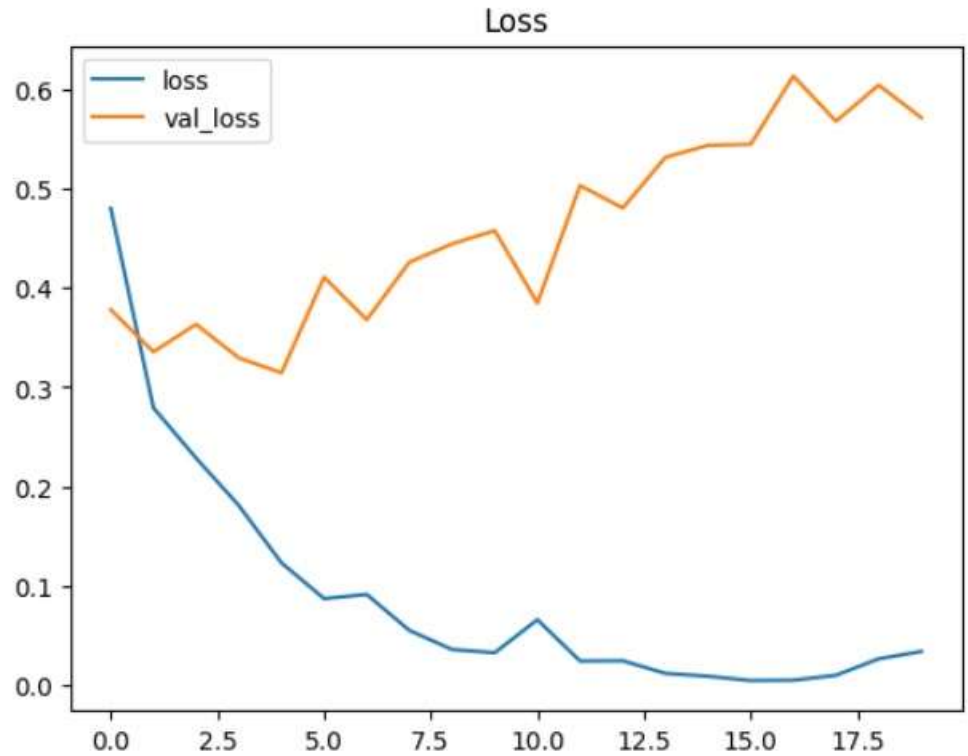

Figure 15: Loss Analysis

4.6 Training & Validation Accuracy

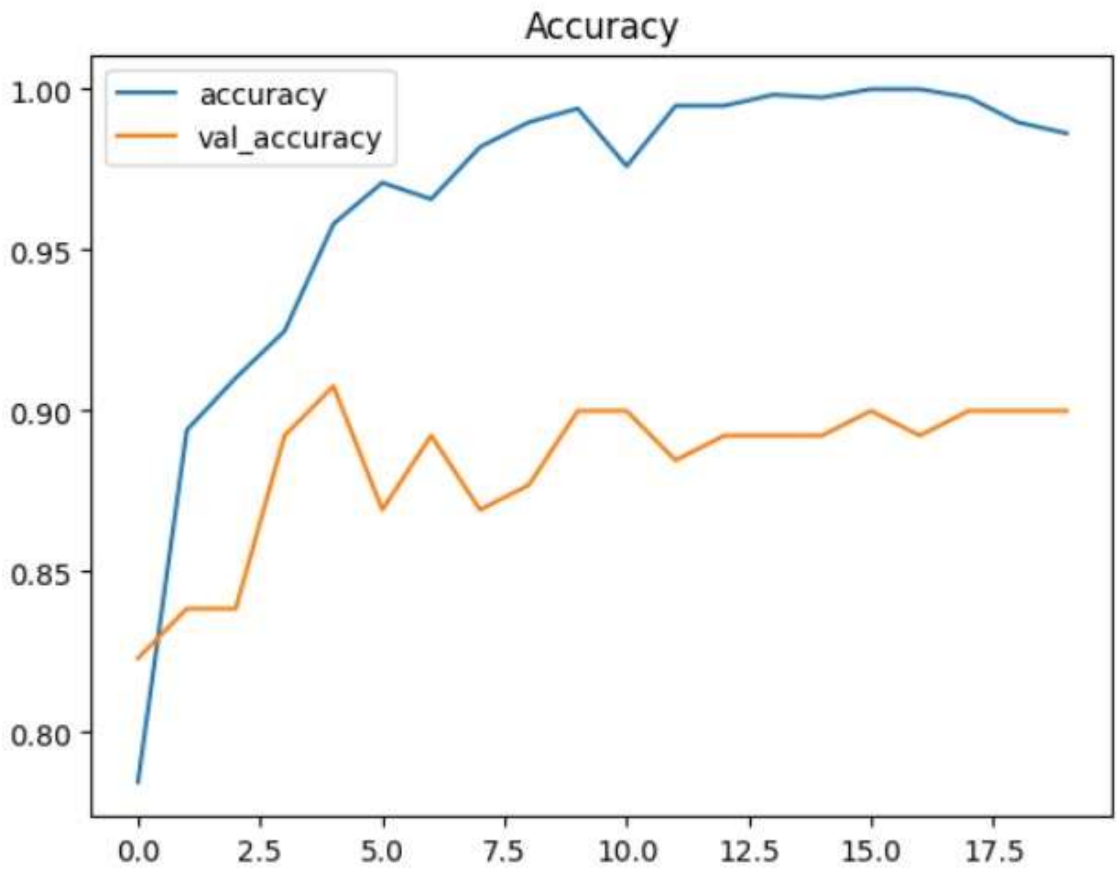

Figure 16: Accuracy Analysis

4.7 Summary of Research Findings

Based on the test outcomes, the model demonstrated superior accuracy with an accuracy rate of 93.6%, surpassing the performance of certain works referenced in Chapter 2 of this paper. The author discovered that the system performed satisfactorily after doing all of the essential black box tests, white box tests and all the performance testing using the confusion matrix. The accuracy for all the three classes which are Benign, Malignant and Normal were obtained as 89.7%, 94.7% and 96.5% respectively. The error rates obtained were as follows, Benign 10.3%, Malignant 5.3% and Normal 3.5%, which then gives an average error rate of 6.4%. The model was also tested using wrong file formats and it produced an error as shown in figure 11 above. The model was also tested for sensitivity and specificity and the average values of the 3 classes was calculated giving an average value of sensitivity as 84.4% and 95.7% for specificity. The 95.7% specificity obtained by the proposed model was way better than that obtained by

Venkatesh et al., (2023) which had 59.4%, and Ciresan et al., (2013) which obtained 85% as stated in Chapter 2.

4.8 Conclusion

In conclusion, the thorough analysis and testing conducted on the proposed research model for breast cancer detection have yielded promising results. With an impressive accuracy rate of 93.6%, surpassing comparable works cited in previous literature, the model demonstrates its efficacy in accurately identifying breast cancer cases. All the results for the performance metrices that were obtained above underscore the potential clinical utility of the proposed model in enhancing breast cancer detection accuracy. The author believes that, further validation studies and refinements could enhance the model's reliability and pave the way for its integration into clinical practice, ultimately contributing to improved patient outcomes in the realm of breast cancer diagnosis and management.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter focuses on conclusions drawn from the research and recommendations for further studies. Also, the analysis aims to ascertain whether the study's objectives were met. Additionally, this chapter delves into the challenges encountered by the researcher during the implementation of the research system under examination.

5.2 Aims and Objectives Realization

The primary goal of this study was to evaluate the effectiveness of utilizing deep learning in the identification of breast cancer in MRI images and to develop a system that employs deep learning for this purpose. The author successfully achieved this aim. Additionally, the objectives outlined by the author were also met. The first objective involved analyzing various deep learning techniques utilized in breast cancer detection. This objective was fulfilled in chapter two, where the author examined different deep learning methods employed in breast cancer detection. The second objective was to create and implement a deep learning model capable of detecting breast cancer using deep convolutional neural networks (DCNN). The researcher achieved this objective by developing a model that utilizes DCNN to identify and classify various tumors in the breast as Benign, Malignant, or Normal. The third and final objective was to assess the effectiveness of DCNN in breast cancer detection and diagnosis. The researcher achieved a validation accuracy of 93.6%, recall/sensitivity, specificity, and error rate of 84.4%, 95.7%, and 0.06 respectively. This represents an improvement over the results obtained by other deep CNN architectures cited in previous studies (Sharma et al., 2020), (Gupta et al., 2019), and (Wang et al., 2022) in terms of accuracy and specificity. Therefore, it is evident that the objectives outlined in chapter one were successfully accomplished.

5.3 Major Conclusions Drawn

The integration of deep learning with MRI images presents numerous advantages in the domain of breast cancer detection. Firstly, deep learning algorithms effectively capture and analyze the intricate patterns and subtle features present in MRI scans, resulting in improved accuracy in identifying potential cancerous tumors. This collaboration enables clinicians to detect abnormalities at earlier stages, facilitating timely interventions and ultimately enhancing patient outcomes. Furthermore, the non-invasive nature of MRI imaging reduces patient discomfort and eliminates the risks associated with traditional screening methods, such as exposure to ionizing radiation. Additionally, the scalability and adaptability of deep learning models allow for continuous refinement and optimization, ensuring the robustness and responsiveness of the detection system to evolving clinical needs.

Moreover, MRI boasts the highest sensitivity for breast cancer detection among other imaging modalities and is indispensable in breast imaging practice. It furnishes valuable diagnostic insights for detecting and characterizing breast abnormalities that may not be adequately visualized with alternative imaging modalities. By leveraging the synergy between deep learning and MRI technology, this research underscores the potential for transformative advancements in breast cancer diagnosis, marking the inception of a new era in precision medicine and personalized healthcare.

5.3 Challenges Faced

During the research, the author encountered challenges in finding the dataset for training the model. Additionally, the time allocated for the project was insufficient, resulting in a system that wasn't as refined as hoped. Another significant challenge was the lack of guidance from health practitioners, which this type of model requires for improvement.

5.4 Recommendations & Future Work

For future enhancements in deep learning-based breast cancer detection using MRI, several recommendations emerge from the insights gained during this research. Firstly, by making use of more powerful and efficient computational machines can significantly reduce training time, especially when handling large and diverse datasets. This would speed up the model development and refinement processes. Additionally, augmenting the training data and increasing the number of neurons in the network can enhance the model's accuracy and predictive capabilities. Furthermore, there's a crucial need to strike a balance between precision and recall to ensure an effective model. While high recall is desirable for comprehensive detection, it must be accompanied by sufficient precision to minimize false positives. Tradeoffs between these metrics should be carefully considered to optimize model performance. In this context, addressing the specific precision shortcomings, such as enhancing it from 83.4% to a higher value, would be essential for refining the model's effectiveness further. By incorporating these recommendations, future research endeavors can advance the state-of-the-art in breast cancer detection, ultimately leading to more accurate and reliable diagnostic tools for improved patient outcomes.

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