

**DEVELOPMENT OF A MOBILE APPLICATION FOR DETECTING  
CERVICAL CANCER USING DEEP LEARNING MODEL**

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**A Project Report Submitted in Partial Fulfillment of the Requirements of the Award of  
the Degree of Master of Science in Embedded and Mobile Systems of the Nelson  
Mandela African Institution of Science and Technology**

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## ABSTRACT


Advancements in technology are significantly enhancing healthcare, particularly in regions with limited clinical expertise, such as Tanzania. Cervical cancer remains a major public health challenge in these areas, where access to regular screening is often inadequate. This project aimed to develop a mobile application powered by deep learning to assist pathologists in detecting cervical cancer without relying on a microscope or physical observation. Traditional diagnostic methods like Pap smears, HPV testing, and colposcopy can be error-prone, especially in resource-limited settings. The dataset comprised 2,276 histological images of cervical tissue, categorized into Grade One, Grade Two, Grade Three, and Not Cancer. These images were collected with permission from SoftMed (T) Limited, a private pathology laboratory in Arusha, Tanzania, and were annotated by qualified pathologists to ensure clinical accuracy. The Design Science Research Methodology (DSRM) was adopted to guide the development and evaluation of the solution. A convolutional neural network (CNN) was implemented for image classification, and several pre-trained models ResNet50, VGG19, MobileNet, and a custom CNN were evaluated. MobileNet was selected due to its high performance and lightweight architecture, ideal for mobile deployment. The final model achieved 99.59% training accuracy and 89.6% validation accuracy. The trained model was integrated into an Android mobile application, enabling healthcare providers to upload and analyze cervical histology images directly from their devices. This application offers a fast, reliable, and accessible diagnostic tool, enhancing cervical cancer screening in underserved areas. The project demonstrates how deep learning and mobile technology can bridge critical gaps in healthcare delivery.

## DECLARATION

I, Dorcas Adam Kiswaga, do hereby declare to the Senate of the Nelson Mandela African Institution of Science and Technology that this project report is my original work and that it has neither been submitted nor is concurrently submitted for a degree award in any other institution.

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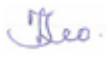
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## CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance by The Nelson Mandela African Institution of Science and Technology, a project report titled *“Development of a Mobile Application for Detecting Cervical Cancer Using Deep Learning Model”* in partial fulfillment of the requirements for the degree of Master of Science in Embedded and Mobile Systems of the Nelson Mandela African Institution of Science and Technology.

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## **DEDICATION**

I dedicate my project report to my loving parents, Mr. Adam Kiswaga, Mrs. Paulina Kiswaga, and my relative, Lugano Kiswaga.

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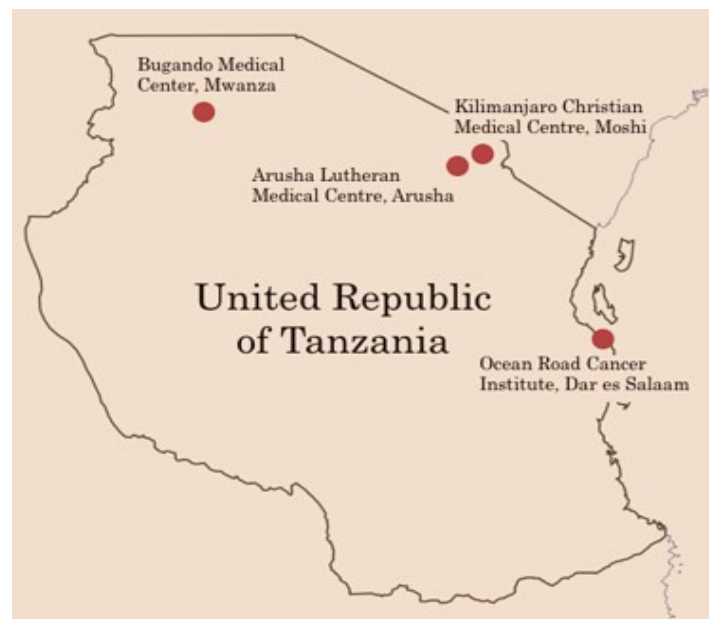
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## CHAPTER ONE

### INTRODUCTION

#### 1.1 Background of the Problem

Disease is an unavoidable aspect of human life and has deeply affected individuals and societies throughout history. With time, progress in medical science and technology has greatly improved the healthcare system, making it easier to detect and treat diseases. In the current digital age, technology is especially important in advancing healthcare, particularly in the early diagnosis of serious conditions like cancer. Detecting cancer at an early stage is vital for effective treatment, higher chances of survival, and improved patient care. Cervical cancer, in particular, continues to be a significant public health issue, especially in low-income regions such as Tanzania, where regular medical screening is often not readily available (Henke *et al.*, 2021). This challenge is compounded by the limited number of cancer care centers in the country, including Bugando Medical Center, Arusha Lutheran Medical Centre, Kilimanjaro Christian Medical Centre, and Ocean Road Cancer Institute. The scarcity of such facilities highlights the need for technological solutions that can support pathologists in diagnosing cancer more effectively. Figure 1 illustrates the geographical locations of the primary medical centers offering cancer care services in Tanzania (Runge *et al.*, 2019).



**Figure 1: Map of Tanzania Showing Cancer Care Medical Centers**

Cervical cancer is one of the leading causes of cancer-related deaths among women globally and continues to pose a serious health challenge in many low-income countries. According to the World Health Organization (WHO), it is the fourth most frequently diagnosed cancer in women and is responsible for a large number of deaths, especially in regions where access to healthcare and routine screening is limited (Bajwa *et al.*, 2021). In Tanzania, the rising number of cervical cancer cases poses a serious public health challenge (*Cervical Cancer*, n.d.), with many women diagnosed at late stages when treatment options are less effective. Detecting cervical cancer early greatly increases the likelihood of effective treatment, helping to lower both illness and death rates. Conventional screening methods such as Pap smears and human papillomavirus (HPV) testing (Cheung *et al.*, 2020) have been successful in identifying pre-cancerous lesions and preventing the progression to cancer (*Cervical Cancer Statistics*, n.d.). These methods have drawbacks, such as requiring highly skilled professionals, being prone to subjective interpretation, and the risk of false positives or negatives. They may not be easily accessible in rural or low-resource areas with limited healthcare services. Consequently, there is increasing interest in developing new technologies to complement current approaches and enhance diagnostic accuracy.

Deep learning methods, especially those utilizing neural networks, have proven highly effective across various domains, including medical diagnostics. These methods can automatically identify complex patterns and features in large datasets, making them well-suited for improving cancer detection. Recent progress in deep learning has shown its ability to accurately interpret medical images and identify abnormalities in different types of cancer, including cervical cancer. Leveraging deep learning for cervical cancer diagnosis is emerging as a promising solution to address gaps in diagnostic capabilities, particularly in areas with limited healthcare infrastructure.

This project aims to address the challenge of cervical cancer detection by developing a mobile application that leverages deep learning to automatically and accurately detect cervical cancer from medical images (Sayed *et al.*, 2018). The proposed solution seeks to provide a scalable, cost-effective tool for pathology healthcare professionals, particularly in low-resource settings (Ofori *et al.*, 2024). By utilizing deep learning, the app can enhance early detection and risk assessment, contributing to better patient outcomes and a reduction in cervical cancer-related deaths (Ahmadzadeh Sarhangi *et al.*, 2024).

Building on prior work in deep learning, cervical cancer detection, and medical imaging, this project seeks to advance efforts against cervical cancer by creating an innovative solution suitable for deployment in resource-limited settings. By leveraging technology, the initiative aims to enhance healthcare quality and save lives, focusing on women in underserved areas.

## 1.2 Statement of the Problem

Cervical cancer represents a major healthcare challenge, particularly for women living in areas with limited resources. Early detection is essential for effective medical intervention and improving survival rates; however, existing screening techniques like Pap smears and HPV tests face limitations in both accuracy and accessibility (Basoya & Anjankar, 2022). In Tanzania, particularly in the Northern Zone, the shortage of high-quality pathology experts contributes to significant delays in the diagnostic process (*Pathology Practice in a Resource-Poor Setting: Mwanza, Tanzania*, n.d.; *The Current State of Pathology in Tanzania*, n.d.). Pathologists' varying skill levels can result in different diagnoses and treatment recommendations. Differences in staining techniques, image quality, and interpretation guidelines between laboratories can also cause inconsistencies in diagnoses. Patients often wait 2 to 3 weeks for test results due to the manual analysis of cervical cancer screenings, which is time-consuming, especially for large volumes of samples, and prone to error. This delays early treatment, increases the risk of disease progression, and reduces treatment success rates (Rendle *et al.*, 2022). Predicting which precancerous lesions will progress to cancer is challenging, leading to unnecessary treatments or missed opportunities for early intervention. Limited healthcare clinical expertise and a shortage of trained pathologists further exacerbate delays in screening and diagnosis. Determining the most effective treatment plan for cervical cancer patients is complex, as it involves multiple factors and potential treatment options. False positives cause unnecessary anxiety and procedures, while false negatives delay critical treatment (Schiffman & de Sanjose, 2019).

The study aims to develop a mobile application that utilizes a deep-learning model to enhance the detection of cervical cancer. Human observation can sometimes lead to errors, so the app seeks to improve existing methods such as HPV testing, colposcopy, histopathology, molecular diagnostics, digital pathology, and liquid biopsy. By integrating these technologies, the app aims to make detection quicker, more accurate, and more accessible, especially in regions with limited clinical expertise (Mudenda *et al.*, 2020).

### **1.3 Rationale of the Study**

Cervical cancer remains a critical health challenge in East Africa, particularly in Tanzania, where it ranks among the leading causes of cancer-related deaths among women. One of the major contributors to this crisis is the shortage of trained pathologists, leading to delayed diagnosis and treatment. Traditional screening methods such as Pap smears, HPV testing, and colposcopy are not only limited in sensitivity and specificity but also require physical infrastructure and skilled personnel, which are often lacking in rural or low-resource areas. Predicting which precancerous lesions will progress to cancer remains a clinical challenge, resulting in both overtreatment and missed diagnoses (Bateman *et al.*, 2019; Makene *et al.*, 2022). These limitations create a critical need for an early detection system that is both accurate and accessible. This project proposes a mobile application powered by a deep learning model trained on histological images of cervical tissue, capable of classifying cases into Grade One, Grade Two, Grade Three, and Not Cancer. Unlike conventional methods, the system provides automated image-based diagnosis directly on the mobile device, without requiring consistent internet access or advanced lab facilities. This enables faster, real-time decision-making at the point of care. Deep learning models have demonstrated superior accuracy in image-based diagnostics and can assist pathologists by minimizing human error caused by fatigue, workload, or inconsistent interpretation (Fekri-Ershad & Alsaffar, 2023; Macios & Nowakowski, 2022; Chandran *et al.*, 2021). By integrating such a model into a mobile platform, the solution becomes not only portable and affordable but also scalable, allowing for widespread deployment in underserved regions. The app supports continuous operation and consistent performance, which is critical in areas with fluctuating access to clinical services. By enhancing diagnostic efficiency, the project reduces the burden on the limited number of healthcare professionals and can be easily adopted by health facilities that lack in-house pathology services. This practical solution supports early intervention and improves survival rates by enabling quicker and more accurate diagnoses. As a result, it offers a forward-looking approach to digital health innovation, especially in low-resource settings where access to specialized medical services is limited.

### **1.4 Project Objectives**

#### **1.4.1 The Main Objective**

The main objective of this project is to develop a mobile application for detecting cervical

cancer using a deep learning model.

#### **1.4.2 Specific Objectives**

The specific objectives of this project are:

- (i) To identify requirements for detecting cervical cancer
- (ii) To develop a deep learning model for detecting cervical cancer according to the requirements
- (iii) To deploy the developed model on a mobile application.
- (iv) To validate the performance of the developed mobile application.

#### **1.5 Research Questions**

The study intended to answer the following questions:

- (i) What are the essential requirements for detecting cervical cancer using image analysis?
- (ii) How can a deep learning model be developed to accurately detect cervical cancer based on identified requirements?
- (iii) How can the developed deep learning model be effectively integrated into a mobile application?
- (iv) How accurate and reliable is the mobile application in detecting cervical cancer when validated with real-world data?

#### **1.6 Significance of the Study**

The study significantly facilitated the development of precise image classification in deep learning models using algorithms that improve cervical cancer detection. The study offers the following advantages:

- (i) The model effectively classified cervical cancer detection, thereby enabling the patient to get treatment on time.
- (ii) The study offered a review of data collection systems in the health sector.

- (iii) Specifically, if the model had been successfully implemented in different pathology centers (since it was a hub for sample processing in the Northern zone), patient outcomes could have been enhanced, and healthcare clinical expertise used more efficiently. This would have addressed the lack of specialized pathology facilities in Arusha, bolstering the local healthcare system and supporting global cervical cancer management efforts.
- (iv) The model helped reduce delays in cervical cancer diagnosis by speeding up the process of analyzing samples, leading to quicker patient care and reducing disease progression risks.
- (v) The model minimized human error, making diagnoses more consistent and reliable across different centers.
- (vi) Supports decision-making for healthcare workers, especially in remote or under-resourced areas.

## **1.7 Limitation of the Project**

This prototype system is specifically designed for trained pathologists who can use a smartphone to capture, crop, and upload images to the main page. It requires users to have the necessary sensory abilities to interpret and diagnose the images. Out of four trained models, the one with the highest accuracy was chosen for implementation. The system supports only the English language.

## CHAPTER TWO

### LITERATURE REVIEW

#### 2.1 Introduction

This chapter offers an overview and explores related studies, focusing on existing technologies and the technical gaps in applying mobile applications with deep learning models for cervical cancer detection. It reviews advancements, challenges in achieving accuracy and accessibility, and the limitations of current methods, setting the stage for developing improved solutions.

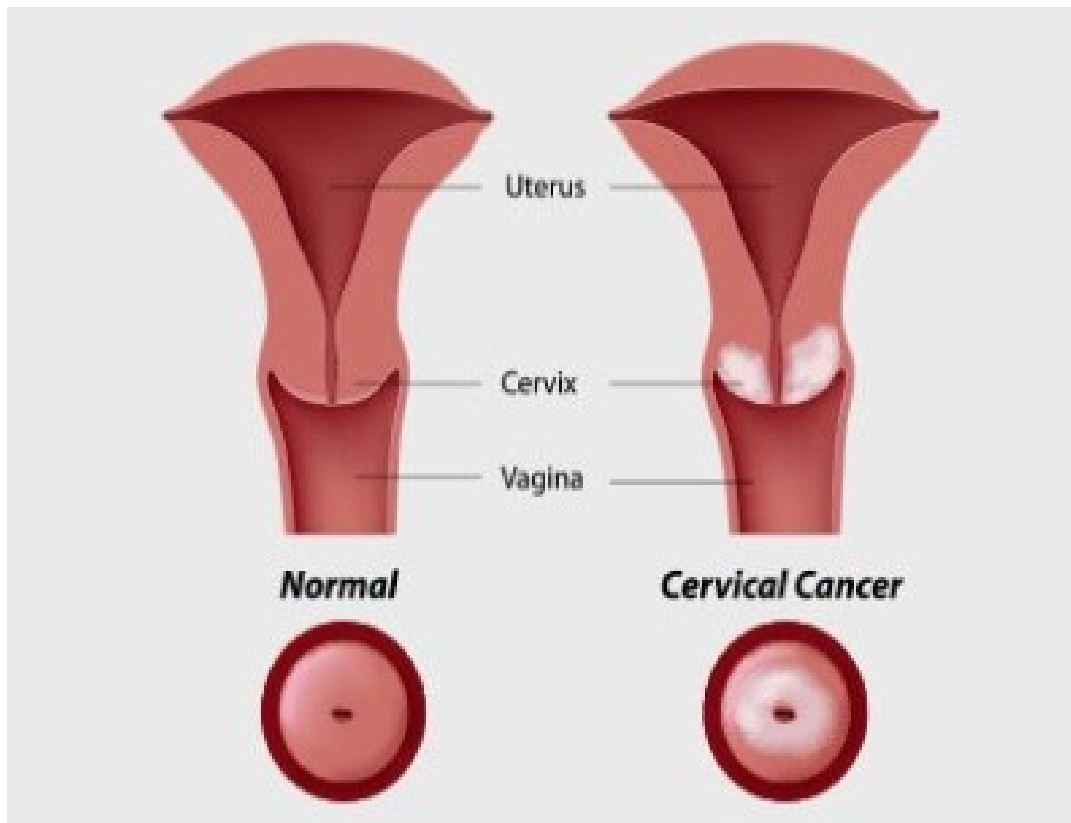
#### 2.2 Details about Cervical Cancer

##### 2.2.1 Definition of Cervix

The cervix is the lower portion of the uterus (womb) that connects to the top of the vagina. It measures approximately 2.5 to 3.5 centimeters (1 to 1.4 inches) in length (*Cervix: MedlinePlus Medical Encyclopedia*, n.d.).

##### 2.2.2 Definition of Cervical Cancer

Cervical cancer begins with abnormal cell growth on the cervix's surface, starting when healthy cervical cells change into precancerous ones. Although not all precancerous cells become cancerous, early detection and treatment are crucial to stop the development of cervical cancer (*Cervical Cancer | Symptoms, Diagnosis and Treatment*, n.d.).



**Figure 2: Cervical Cancer**

### 2.2.3 Types of Cervical Cancer

Cervical cancer is mainly divided into two types of carcinoma:

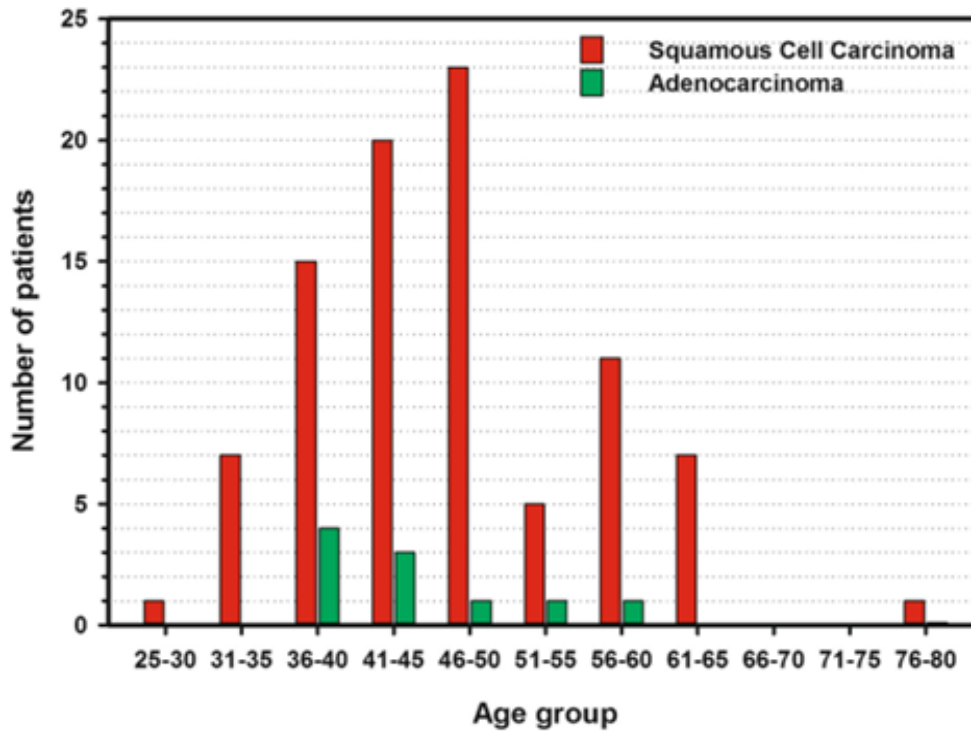
#### (i) Squamous cell Carcinomas

Squamous cell carcinoma originates in the thin, flat squamous cells forming the cervix's outer layer. This type accounts for approximately 80% to 90% of all cervical cancers (*Comprehensive Guide to Cervix Cancer Symptoms & Stages* | Omega Hospitals, n.d.). This can be further categorized based on the level of differentiation: Grade 1 is referred to as well-differentiated or low-grade, Grade 2 as moderately differentiated, and Grade 3 as poorly differentiated or high-grade (*Grading and Staging of Cancer - Health Encyclopedia - University of Rochester Medical Center*, n.d.; *Types And Grades Of Womb Cancer* | Cancer Research UK, n.d.).

#### (ii) Adenocarcinomas

Adenocarcinoma, by contrast, originates in the column-shaped glandular cells lining the cervical canal and accounts for 10% to 20% of cervical cancer cases (*Cervical Cancer - Radiation Oncology*, n.d.; *Types and Grades of Cervical Cancer* | Cancer Research UK, n.d.).

Subtypes include end cervical adenocarcinoma, endometriosis adenocarcinoma, and clear cell adenocarcinoma (Stewart *et al.*, 2019).



**Figure 3: Distribution of Squamous Cell Carcinoma and Adenocarcinoma Age**

The graph in Fig. 3 illustrates that Squamous Cell Carcinoma (SCC) is significantly more prevalent than Adenocarcinoma across all age groups, with the highest incidence observed in individuals aged 41–50. Squamous Cell Carcinoma (SCC) impacts a broader population, highlighting its importance (Alsbeih *et al.*, 2013). Focusing on Squamous Cell Carcinoma (SCC) addresses the most common form of cervical cancer and optimizes the use of resources for projects and treatment efforts.

#### 2.2.4 Cervical Cancer Screening

Cervical cancer screening aims to identify abnormal cervical cells or early signs of cervical cancer at a stage when treatment is more effective and chances of a cure are higher. Screening identifies cell changes in the cervix that could potentially develop into cancer. This process helps prevent cervical cancer and save lives. Common screening methods include the HPV test and the Pap test, which can identify pre-cancerous changes that can be treated to stop cancer from developing (*The Pap (Papanicolaou) Test | Cervical Cancer Screening Test | American Cancer Society, n.d.*; *The HPV Test | Cervical Cancer Screening Test | American Cancer Society, n.d.*). Screening typically involves cervical cytology, the Pap smear or Pap test, HPV

testing, or a combination of both. Regular screening is recommended for most women (*Cervical Cancer Screening* | ACOG, n.d.).

### 2.2.5 Microscopic Anatomy

Microscopic anatomy in cervical cancer focuses on the in-depth study of cervical tissues and cells at a microscopic level to detect and assess cancerous changes. It involves examining cell morphology and tissue structure and recognizing abnormal patterns of cell growth.

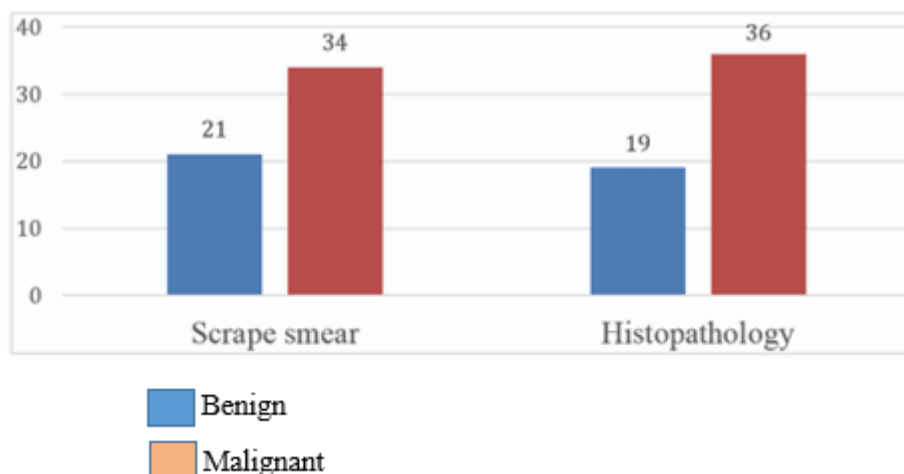
Key aspects studied in microscopic anatomy for cervical cancer include:

#### (i) Cytology

Cytology: Examining individual cervical cells, often through Pap or Scrape smears, to detect pre-cancerous and cancerous changes (Ramírez *et al.*, 2023).

#### (ii) Histology

Histology involves examining tissue samples from the cervix, usually collected through biopsies, to analyze the structure and arrangement of cells. This helps identify different types of cervical cancer, such as squamous cell carcinoma and adenocarcinoma (Jenkins, 2020).



**Figure 4: Pap or Scrape Smear and Histopathological** (Tumors, 2020)

The graph in Fig. 4 shows that histopathology finds more malignant cases (36) compared to scrape smear (34) and fewer benign cases (19 compared to 21). This means histopathology is more accurate and better at detecting cancer. Choosing histology ensures a more reliable method for identifying cervical cancer early and correctly.

## 2.3 Related Works on Cervical Cancer

### 2.3.1 Using Deep Learning to Detect Cervical Cancer

Attallah (2023) recent research has increasingly explored the use of deep learning for cervical cancer diagnosis. One significant study implemented a Computer-Aided Diagnosis (CAD) system that combined multiple CNN architectures to extract features, resulting in a 3.2% improvement in the F1 score compared to models based on a single architecture. This highlights the potential of ensemble deep learning methods in boosting diagnostic accuracy. The study assessed various CNN models, including DarkNet-19, DarkNet-53, Inception V3, MobileNet V2, and Inception ResNet V2. Although detailed performance metrics for individual models were not provided, the research offered meaningful contributions to the use of deep learning in medical image analysis. Nevertheless, it had some shortcomings, such as not specifying data splitting methods, omitting optimizer details, and lacking a deployment plan for practical use. In contrast, the current project addresses these limitations by using a MobileNet based model tailored for real-time, offline deployment via a mobile application specifically designed for low-resource settings where access to clinical expertise is limited.

Hou *et al.* (2022) recent studies have demonstrated the effectiveness of Artificial Intelligence (AI) techniques such as Graph Convolutional Networks (GCNs) and Convolutional Neural Networks (CNNs) in cervical cancer detection. These models automate the processes of image analysis, feature extraction, and classification, achieving improved accuracy and sensitivity often exceeding 90% compared to traditional methods like Pap smears and colposcopy. Deep feature fusion techniques have also enhanced performance by capturing both spatial and contextual image information. While these AI methods offer significant improvements in diagnostic reliability and can assist in addressing the shortage of medical specialists, challenges remain. These include the need for large annotated datasets, handling of overlapping cells and staining variability, and ensuring secure data management. Furthermore, clinical validation and real-world deployment are still limited. The current project builds on this foundation by implementing and deploying a MobileNet based model in a mobile application, offering real-time, offline cervical cancer screening suitable for low-resource healthcare settings.

Chen *et al.* (2021) the "Cervical Cancer Screening System Based on Deep Learning Technology," known as CytoBrain, is designed to enhance the detection of abnormal cervical cells through an integrated AI approach. It comprises three main components: cervical cell

segmentation, cell classification using the CompactVGG model, and a visual diagnostic aid. The system has demonstrated potential in improving diagnostic support, particularly through the CompactVGG classifier, which achieved encouraging preliminary results in terms of classification accuracy. Despite this promise, CytoBrain faces several challenges. These include reliance on a limited dataset, lack of expert-labeled images, and difficulty in handling overlapping nuclei and clustered cells. The absence of a validation dataset increases the risk of overfitting, and no evidence of real-world deployment has been reported. Nevertheless, CytoBrain illustrates how deep learning can be integrated into automated cervical screening tools, offering a foundation for systems like the one developed in this project. Unlike CytoBrain, this study focuses on building a clinically relevant, mobile-based diagnostic tool using MobileNet, optimized for real-time use in low-resource environments.

Tripathi *et al.* (2021) a recent study utilized the SIPAKMED dataset to train a deep learning model for classifying cervical cells into five categories. Among the models tested, ResNet-150 achieved the highest classification accuracy of 94.89%, demonstrating its effectiveness in detecting abnormalities in Pap smear images. This confirms the potential of deep CNN architectures in improving diagnostic precision. However, the study's reliance on a single dataset raises concerns about generalizability to other image types. It also lacked practical deployment strategies and did not address challenges such as overlapping cell structures or real-world usability. Despite these limitations, the study provides important insights into deep learning's role in automated cervical cancer screening. Unlike this work, the current project expands beyond cell classification to histological grading and real-time mobile deployment, offering a more accessible and clinically applicable solution.

Anaya-Isaza *et al.* (2021) to improve medical image classification and segmentation using deep learning to help with diagnosis and treatment, especially when data is limited and overfitting is a concern. The techniques used include regularization methods and residual connections to boost model performance. The study also suggests using batch normalization to address issues with internal covariates, which helps improve gradient flow and acts as regularization. The limitation is that batch normalization may not work well with dropout in some model designs, which could reduce the model's effectiveness. Details about the deployment were not mentioned.

Sørbye *et al.* (2023) the study aims to find better ways to prevent cervical cancer in areas with limited access to screening and HPV vaccination, focusing on South African women. It uses a

“test-and-treat” strategy with mRNA HPV tests to improve prevention, looking at different HPV types to find the best ones for screening, especially for women with high HIV rates. However, there are some limitations. Since the study mostly involved HIV-positive women with little past screening, the results may not apply to all women and could be biased. There is also a risk of overtreatment if all CIN3 lesions are handled the same way without considering different HPV types. More research is needed to improve this method. Also, the dataset was not divided into training and validation sets, and there were no details about real-world use (deployment).

According to Darwish *et al.* (2023) the goal is to improve how accurately pre-cancerous cervical lesions are classified using advanced Vision Transformer technology. This system aims to better detect small differences in colposcopy images and support human experts in diagnosis. The model was trained on a Kaggle dataset and uses Vision Transformer technology with shifted patch tokenization to learn unique features of different cervical lesions. It achieved 91% accuracy, which is better than other models. However, there are some limitations. The study looks back at existing data, so more studies are needed for future validation. It also lacks detailed clinical information, which could help in analysis, and there’s a risk of overfitting due to limited training data. Training on a larger dataset could improve the model, especially for handling images with metal objects and better identifying Type 3 colposcopy images. There was no information provided about how the model would be used in real life (deployment)

### **2.3.2 Mobile Applications that deploy Deep Learning models for Cervical Cancer Detection**

Mohebi *et al.* (2018) a similar study centered on creating a mobile application intended to raise awareness and boost participation in cervical cancer screening. The app was designed to enhance public knowledge by offering easily accessible, expert-approved information and motivating users to engage in preventive healthcare. Early assessments showed that users found the app easy to use, positively received it, and it showed promise in supporting health education efforts. However, the study was conducted with a small sample in Isfahan, Iran, which limits its generalizability. Factors such as limited smartphone or internet access may reduce its reach, especially in rural areas. The study also did not assess the long-term impact of the app on actual screening rates or health outcomes. Nonetheless, it highlights the important role mobile health (mHealth) solutions can play in improving cancer awareness and prevention, a concept expanded in the current project by integrating AI-powered diagnosis with mobile accessibility.

Aprina *et al.* (2024) the DEDIKASI app was created to enhance early detection and awareness of cervical cancer among women in underserved areas of Indonesia. It offers self-assessment features, educational content, and guidance to promote proactive health behaviour. Tested among 388 women of reproductive age, the app proved effective in raising awareness and encouraging preventive screening. Its user-friendly interface and locally tailored health information contributed to its accessibility. The app's reliance on self-reported data may lead to inaccuracies, and the limited geographic and demographic scope of the study affects how broadly the findings can be applied. Despite these challenges, DEDIKASI highlights the potential of mobile health tools to inform users and support early risk recognition. Building upon this, the current project advances the concept by integrating automated image analysis, shifting from education and awareness to AI-powered detection and classification of cervical cancer.

Mosiichuk *et al.* (2023) a recent study proposed an AI-driven solution to enhance cervical cancer screening in low-resource settings using mobile microscope images. The model employed a RetinaNet architecture with a ResNet50 backbone, designed to detect cervical lesions based on the Bethesda System (TBS). This nucleus-focused deep learning approach was developed for deployment on mobile devices, aiming to bring real-time diagnostic assistance to underserved regions. The approach demonstrates significant promise, particularly in leveraging object detection frameworks for cytological analysis. However, the study faced challenges related to dataset size and diversity, which may limit its generalizability and clinical robustness. Further validation on larger and more heterogeneous datasets is required to ensure consistent performance across populations. Nevertheless, the work provides a valuable precedent for mobile-integrated AI in cervical cancer screening a vision aligned with the current project, which similarly integrates deep learning and mobile platforms for accessible and accurate diagnosis.

Sami *et al.* (2022) one study explored the use of Smartphone-Based Digital Visual Inspection with Acetic Acid (D-VIA) to enhance cervical cancer screening in low-resource settings. The method involves capturing cervical images before and after applying acetic acid, allowing healthcare providers, with or without expert assistance, to detect lesions and make prompt treatment decisions. The system also supports real-time consultation with specialists, improving diagnostic confidence and extending expert access to remote areas. Initial findings demonstrated technical feasibility and usability, with smartphones successfully capturing

diagnostic-quality images suitable for clinical review. However, the study lacked real-world implementation and did not fully address broader systemic challenges such as patient access, healthcare infrastructure, and provider training. Despite these limitations, D-VIA shows how digital tools can facilitate cervical screening in underserved environments. The current project builds upon this direction by incorporating deep learning to automate lesion grading and providing instant results directly on mobile devices, improving both accessibility and diagnostic accuracy.

Bae *et al.* (2020) cervical cancer screening in low-resource settings faces challenges such as limited infrastructure, few trained personnel, and costly diagnostic tools like colposcopes. Traditional VIA lacks consistent accuracy, making it unreliable. To address this, a smartphone-based endoscopic system with machine learning (e.g., KNN) has been proposed to automate VIA screening. This approach captures high-resolution images, classifies tissue, and provides visual feedback, offering a cost-effective and scalable solution. However, limitations include a small dataset, segmentation challenges, image quality issues, and potential performance drop with larger, diverse populations

## **2.4 The Technical Gap**

Traditional methods for diagnosing cervical cancer, such as Pap smear tests, HPV testing, and colposcopy, can be prone to errors and may miss serious cases. Deep learning models often have complex architectures with numerous layers and parameters, leading to reduced accuracy and requiring significant computational power and extended training time Sarker (2021). Many of these models also face difficulties in effectively interpreting images (Gkelios *et al.*, 2021). In mobile applications, datasets and models are primarily used for raising awareness rather than for extensive training. Although a method based on the Bethesda System (TBS) ((4) *Designing an Effective User Interface for a Mobile Application*, n.d.) is employed to identify lesions, many trained models have yet to be deployed in pathology.

## CHAPTER THREE

### MATERIALS AND METHODS

#### 3.1 Introduction

This chapter covers the materials and methods utilized for conducting the project study, including the case study and scope, project methods, target processes, system requirements, data analysis, model training, transfer learning, development approach, system development, model deployment, and system testing and validation.

#### 3.2 Project Case Study and Scope

The project was conducted at SoftMed (T) Limited in Arusha, chosen because it's the only private pathology lab in Northern Tanzania. This made it easier to collect the necessary data. Also, other images of not-cervical cancer were collected through Google. The project focused specifically on diagnosing cervical cancer by analyzing histology images classified into grade 1, grade 2, grade 3, and not cancer. These images were used to make the model more precise. The deep learning model developed was put only into a mobile app that helps pathologists to easily upload or capture images for the model to analyse, and provide feedback on the stage of cervical cancer. The goal was to make the diagnostic tool more accessible by focusing on the mobile app, aiming to overcome the limitations of current pathology technologies.

#### 3.3 Project Methods

The project employed both qualitative and quantitative methods for data collection and analysis. In qualitative research, the focus was on exploring the depth and context of images and models, whereas quantitative research concentrated on measurement, numerical data, and statistical analysis to conclude.

The qualitative methods included reviewing research papers and publications on cervical cancer detection and deep learning, conducting interviews with pathology experts in the field, as shown in Appendix One, and observing how screenings are performed and how various stages of cervical cancer are diagnosed. In quantitative methods, a structured questionnaire was provided to pathologists to collect feedback, as shown in Appendix two.

### **3.4 Target Process**

This project focused solely on cervical cancer and targeted pathologists who can interpret and diagnose different images of cervical cancer and provide detailed explanations about the disease.

### **3.5 Requirements**

#### **3.5.1 Data Collection Tools**

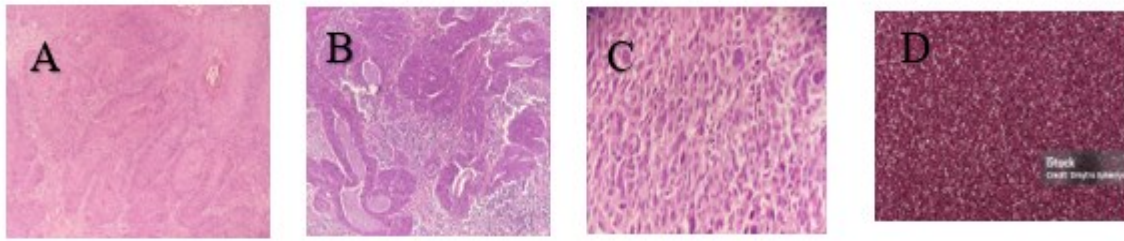
Collecting and managing data significantly influences the project's success. By using a Samsung smartphone camera with megapixels of 12 and above and microscopic imaging at the SoftMed Pathology lab, the dataset image for the model was gathered and grouped into grades 1, 2, and 3 from hematoxylin and Eosin-stained slides were obtained, ensuring high-quality imaging to represent cellular features faithfully. Every photograph was carefully chosen to showcase different examples of cellular shape, and the process of collecting the images included modifying the lighting and focus to get maximum clarity; also, other images of not cervical cancer were collected through Google. After the image capture, the photos were loaded into a computer for analysis, where they received pre-processing, organization, and labelling to prepare for model training. By taking these steps, the aim was to ensure the dataset was robust and accurately represented the different phases of cervical cancer.

### **3.6 Data Analysis**

#### **3.6.1 Image Preprocessing**

Image preprocessing involves enhancing raw image data to improve its quality before feeding it into a deep learning model. In this project, the dataset was preprocessed to allow the model to intelligently extract relevant features for diagnosis. This process included loading the dataset to ensure proper labeling and organization into their respective classes, that is, grades 1, 2, 3, and not cancer. The images were then visualized to gain insights into the data, resized to 224 x 224 pixels, and the pixel values were normalized within the range of 0-1 by dividing by 255 to scale the data (*The Complete Guide to Image Preprocessing Techniques in Python* | by Maahi Patel | Medium, n.d.; *The Role of Data Preprocessing in Machine Learning* | by Skillfloor | Medium, n.d.; *The Role of Data Preprocessing in Machine Learning* | by Skillfloor | Medium, n.d.). Figure 5: Examples of different histological stages of cervical cancer: (A) represents

Grade 1; (B) represents Grade 2; (C) represents Grade 3; and (D) represent Not Cancer Labelled image by the expert.



**Figure 5: Histology Image of Cervical Cancer Stages**

### 3.6.2 Augmentation

Deep convolutional neural networks require a large amount of training data to effectively learn features from images and achieve high accuracy when classifying new, unseen data (*The Role of Data Preprocessing in Machine Learning*, n.d.). Because of time and resource constraints in this study, it was not possible to gather enough data for thorough training. Using a small dataset for training can lead to overfitting, where the model learns the training data too well but struggles to perform accurately on new or unseen data (Taye, 2023; Ghoneim *et al.*, 2020). To address this issue, data augmentation techniques are employed to create additional data samples and reduce overfitting. The ImageDataGenerator class was used to perform image augmentation during the generation of training data, as shown below.

- (i) **Rotation:** To generate more training samples, images were rotated with a 0.7 probability. The rotation was limited to a maximum of 10 degrees to the left and 10 degrees to the right.
- (ii) **Flipping:** Images were mirrored horizontally and vertically to generate variations.
- (iii) **Zooming:** Enlargements of image sections were performed, with a probability of 0.3. A maximum zoom factor of 1.6 and a minimum zoom factor of 1.1 were applied.
- (iv) **Rescaling:** The pixel values of the images were standardized by applying a rescaling factor of 0.25 for normalization

Each image was augmented multiple times to create varied versions, which expanded the dataset and improved the model's ability to generalize and recognize new, unseen images.

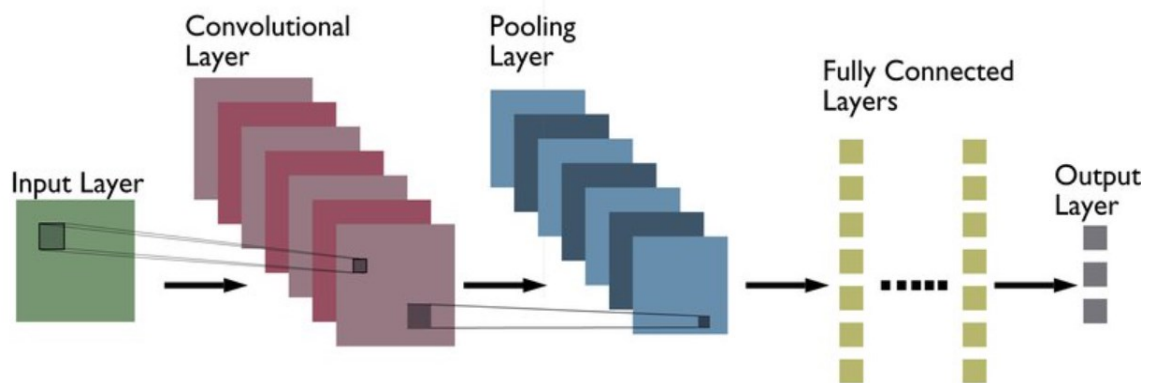
### 3.6.3 Splitting the Dataset

The images used in this study were divided into 80% for training and 20% for validation sets to facilitate model development and evaluation.

## 3.7 Model Training

### 3.7.1 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are a type of deep learning model designed to automatically and efficiently recognise patterns and features in image data. They achieve this through a combination of convolutional filters, activation functions, and pooling operations (Taye, 2023). CNNs are particularly effective at analyzing visual data, such as cervical cancer images (Ghoneim *et al.*, 2020). A CNN model was developed to classify cervical histology images into four categories: Grade 1, Grade 2, Grade 3, and Not Cancer. Figure 6 illustrates the operational process of the CNN (*Different Types of CNN Architectures Explained: Examples*, n.d.). The input layer receives the cervical image, which is then passed through the convolutional layers that apply filters to detect critical features such as edges, textures, and shapes associated with cancerous changes. The pooling layers reduce the spatial dimensions of the feature maps while retaining the most important information, thereby enhancing computational efficiency. In the fully connected layers, the extracted features are combined to form a high-level representation of the image. Finally, the output layer generates the classification result, indicating whether the image is cancerous and, if so, identifying the corresponding stage (Grade 1, Grade 2, or Grade 3).



**Figure 6: Convolutional Neural Network Architecture**

### 3.8 Transfer Learning

Transfer learning utilizes pre-trained Convolutional Neural Network (CNN) models, which are networks trained on large datasets for general image recognition tasks and made available for further use (Patil & Rane, 2021). This approach is beneficial when there is limited labeled data to train a new model. It reduces the time and computational resources required since there is no need to start from scratch (Hosseini *et al.*, 2023). The use of pre-trained models offers two main advantages: first, they perform well across both large and small datasets. Second, applying these pre-trained models helps minimize overfitting, especially when working with limited datasets (Kolides *et al.*, 2023). The details of the pre-trained models used in the project are provided in the subsection.

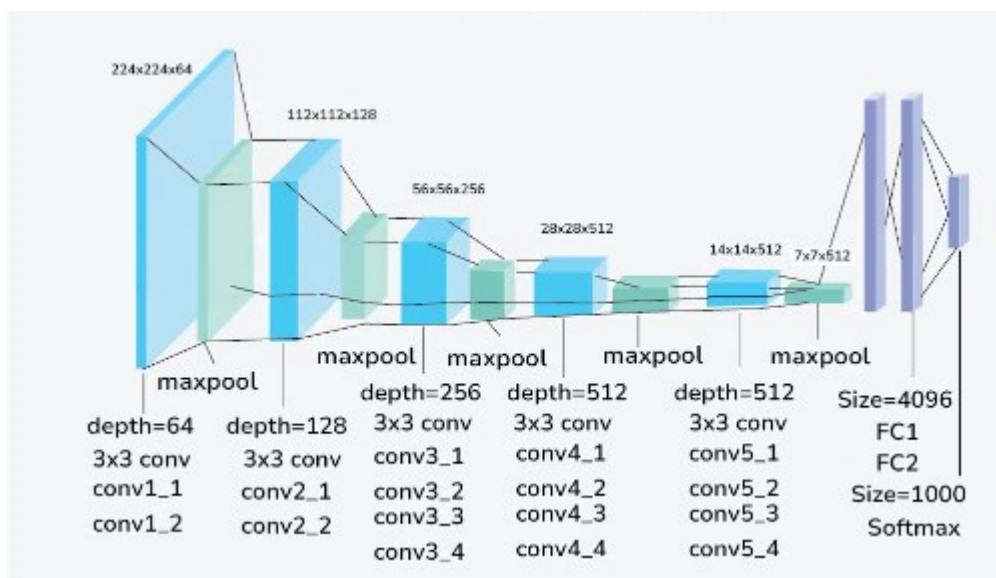
#### 3.8.1 MobileNet

MobileNet is a deep learning model that efficiently runs on low-power devices with fewer parameters, enabling fast processing for real-time applications. It is a good choice for detecting cervical cancer because it is lightweight, which means it can process data quickly and use less power. Despite its small size, it provides high accuracy, which is important for correctly detecting cervical cancer. It is flexible and can be adjusted for different tasks, making it useful even when there is limited data (Mathivanan *et al.*, 2024). The MobileNet model was designed with four classes: "Grade 1," "Grade 2," "Grade 3", and "Not Cancer". It takes an input image resized to 224x224 pixels and uses convolution layers to capture basic features. A Rectified Linear Unit (ReLU) function aids the model in learning complex patterns, followed by a pooling layer that decreases data size while preserving essential information. A softmax layer outputs probabilities for each class, helping the model predict the image's label (*DLOA (Part-20)-MobileNet CNN and Implementation | by Dewansh Singh | Medium, n.d.*).

#### 3.8.2 Visual Geometry Group (VGG-19)

Visual Geometry Group (VGG19) is a convolutional neural network model used for image classification and feature extraction. Its architecture is designed to recognize intricate features in images, making it highly effective for accurately detecting different grades of cervical cancer. VGG19 has been widely used in various image classification tasks, showcasing its reliability (*VGG19 Architecture for Binary Classification VGG19 Is an Extension of.. | Download Scientific Diagram, n.d.*). Its design focuses on enhancing feature extraction, allowing the model to distinguish between different cancer grades. The VGG19 model was

developed with four classes: "Grade 1," "Grade 2," "Grade 3," and "Not Cancer." Figure 7 illustrates the workflow of a VGG19 model. The model consists of 19 layers, primarily convolutional layers, which process and learn patterns from images. The input image is resized to 224x224 pixels with three color channels (RGB). It employs small 3x3 filters across 16 convolution layers, followed by a Rectified Linear Unit (ReLU) activation function to help the model identify complex patterns. After each block, a max-pooling layer reduces the data size for increased efficiency. The flattened output is then passed through three fully connected layers for making predictions, with a softmax layer generating probabilities for each class (Sikar *et al.*, 2025).

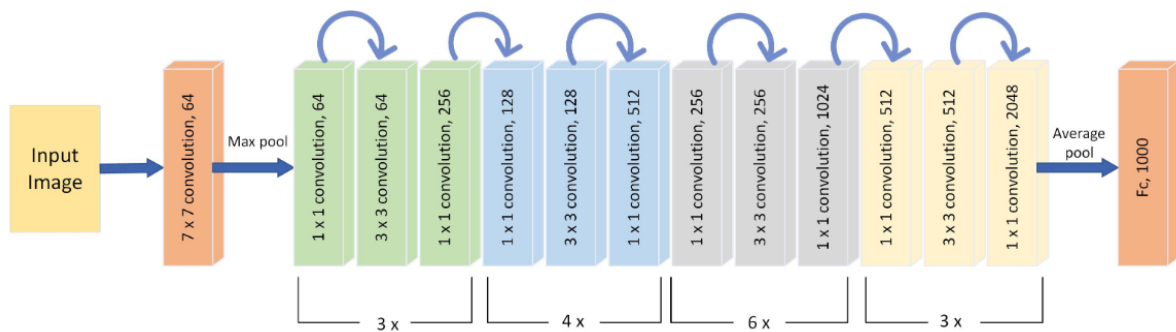


**Figure 7: VGG-19 Architecture** (*VGG-Net Architecture Explained - GeeksforGeeks, n.d.*)

### 3.8.3 ResNet50

ResNet50 is a deep learning model specifically tailored for image classification, consisting of 50 layers that include convolutional and pooling layers. It is well-suited for detecting cervical cancer as it facilitates the training of deeper networks, allowing for the learning of intricate features, which enhances classification accuracy (Ahmadzadeh Sarhangi *et al.*, 2024b). ResNet50 has shown strong performance in image recognition challenges, making it an excellent choice for medical imaging tasks. Its flexible architecture supports transfer learning, enabling improved performance on specific datasets by leveraging features acquired from larger datasets. The model uses skip connections, which allow input data to bypass certain layers and connect directly to deeper layers. This design improves gradient flow and helps address the vanishing gradient issue (*Residual Networks (ResNet) - Deep Learning -*

GeeksforGeeks, n.d.). Each Residual Block includes two or three convolutional layers, batch normalization to speed up training, the ReLU activation function, and a skip connection that adds the input back into the output. ResNet50 also features a bottleneck structure with three convolutional layers, which helps reduce the number of parameters and increase efficiency. Instead of fully connected layers, it applies global average pooling to simplify feature maps and reduce the risk of overfitting. Pre-trained on large datasets like ImageNet, ResNet50 can be fine-tuned on smaller, domain-specific datasets, making use of previously learned features to enhance performance (*What Is Component Testing? The Foundation of Software Quality*, n.d.).



**Figure 8: Resnet50 Architecture**

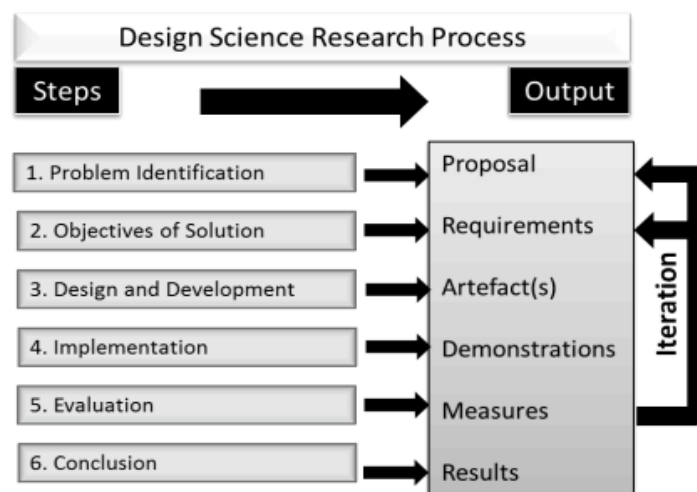
### 3.9 Development Approach

In this project, system development involves the creation, design, construction, and implementation of software applications focused on the early detection of cervical cancer. It follows a systematic and organized process that includes multiple stages, from initial planning to final deployment. The goal was to develop a model that is efficient, functional, and dependable, meeting the specific needs of its users

#### 3.9.1 Model Development Methodology

The Design Science Research Methodology (DSRM) was chosen for this project because it focuses on solving problems through the creation and analysis of technological artefacts. This approach emphasizes combining theoretical concepts with practical applications. The process begins with problem identification, where the research challenge is defined, followed by establishing the objectives of the solution and outlining the goals of the proposed solution. In the design and development phase, the solution is designed and built, which then moves into implementation, where the solution is put into practice. The evaluation phase assesses the solution's effectiveness, ensuring it meets the objectives and performs as intended. Finally, the

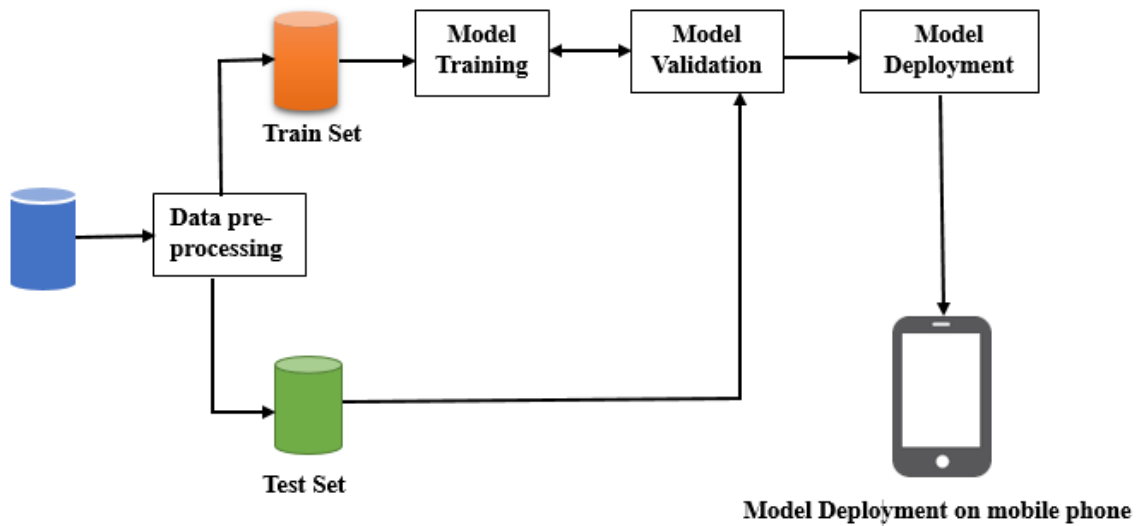
conclusion summarizes the findings and provides recommendations. The process is iterative, with feedback from the evaluation feeding back into earlier stages to refine and improve the solution. Throughout the process, various outputs are generated, such as proposals, requirements, artefacts, and results, which contribute to the final research documentation. An example of applying this methodology is the development of a model for cervical cancer diagnosis, which can lead to effective solutions like early intervention and disease management (Williams, 2007; Ardakan & Mohajeri, 2009). Figure 9 illustrates the steps involved in the Design Science Research process, starting with problem identification and progressing through to the conclusion.



**Figure 9: Design Science Research Process** (Mtsweni *et al.*, 2014)

### 3.9.2 System Design

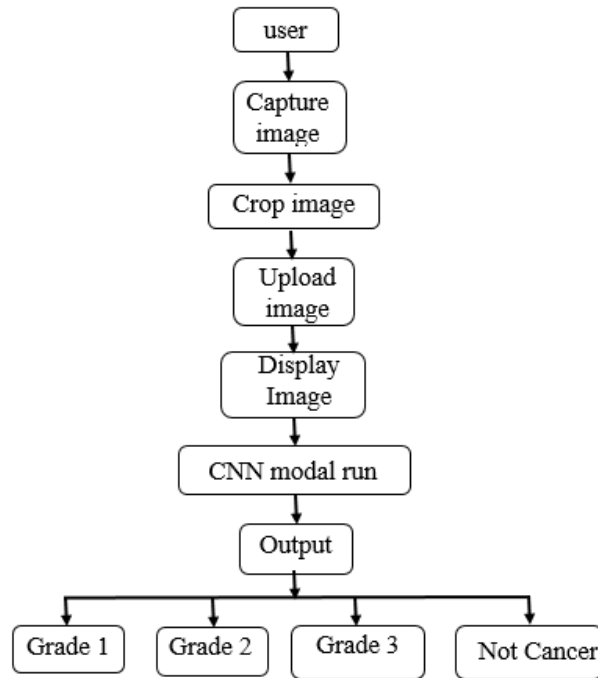
System Design outlines the steps for the project, including data collection, preprocessing, model development, testing, and deploying the model on a mobile app. Figure 10 illustrates the workflow, which begins with the cervical cancer dataset, which is preprocessed and divided into training and testing sets. The training set was used to train and validate the model, while the testing set assessed the model's performance. The model was deployed on a mobile phone for pathology predictions.



**Figure 10: Conceptual Design of the System**

### 3.9.3 Flow Chart Diagram

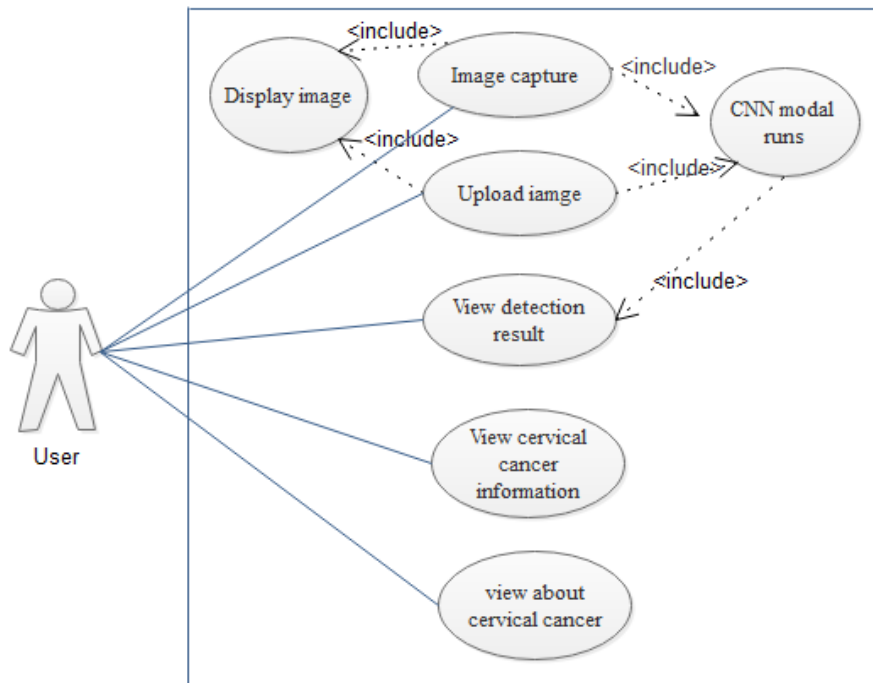
The flow chart visually represents the steps or processes required to complete a task or solve a problem. The process begins with the user or pathologist capturing an image using the camera and uploading it. The image then proceeds to a cropping stage to remove unnecessary elements before being displayed on the phone's main page for processing. The model analyzes the image and provides a diagnosis, identifying it as Grade 1, Grade 2, Grade 3, or Not Cancer. This enables the user or pathologist to interpret the diagnosis. Figure 11 illustrates the flow of data throughout this process.



**Figure 11: Flow Chart Diagram**

### 3.9.4 Use Case Diagram

A use-case diagram illustrates the activities performed by the system's users. It includes the use cases or specific tasks, the actors or users involved, and the relationships between them. The pathology can capture or upload the image, which automatically appears on the main page. The model then processes the image and displays the detection results. The pathologist can access detailed information about cervical cancer detection and learn more about the disease. Figure 12 shows the use case diagram for the cervical cancer detection mobile application.



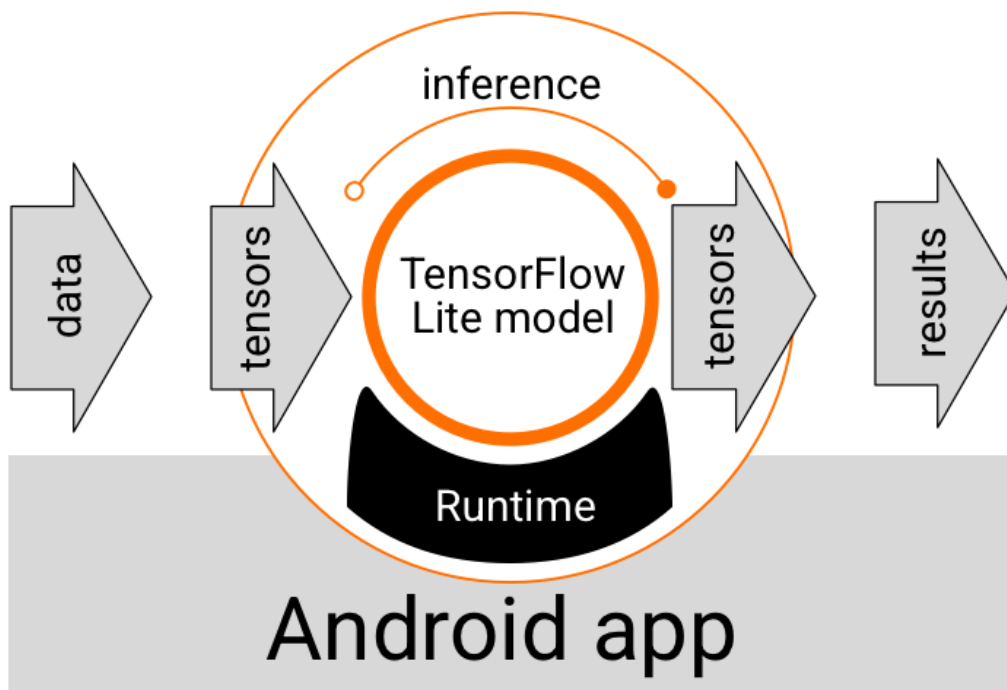
**Figure 12: User Case Diagram**

### 3.10 System Development

The system development utilized TensorFlow, an open-source platform, to implement complex neural networks with multiple layers. The Keras library was used to build and evaluate deep learning models. Google Colab served as the computing environment for training and testing, with Python 3 employed for all coding and scripting tasks. Visual Studio Code was used to develop a mobile application for deploying the model.

### 3.11 Model Deployment

The model was deployed on a mobile application after being converted to TensorFlow Lite, following its training in TensorFlow. This TensorFlow Lite model, operating within an Android app, processes input data and predicts the grade of cervical cancer (1, 2, and 3) or not cancer. The input data is formatted as tensors, and the model generates new tensors with the prediction results, which the app then displays to the user, allowing them to understand the cancer grade in the tissue (*LiteRT for Android* | *Google AI Edge* | *Google AI for Developers*, n.d.).



**Figure 13: Execution Flow for TensorFlow Lite Models in Android Apps**

### 3.12 System Testing and Validation of Performance of the Developed Mobile Application

System testing involved testing components of the model, such as layers, activation, and loss functions, to ensure that they all worked together as intended (*System Testing - Software Engineering - GeeksforGeeks*, n.d.). This involved evaluating the model's performance on a representative dataset to ensure it achieved the desired outcomes and performed well across different situations (*Evaluating Model Performance: A Comprehensive Guide | by Zhong Hong | Medium*, n.d.). Once tested, the system was validated through user acceptance testing to ensure the expected results were accurate and to verify that the model met the defined requirements and was ready for deployment (*What Is User Acceptance Testing (UAT)? | Definition from TechTarget*, n.d.).

## CHAPTER FOUR

### RESULTS AND DISCUSSION

#### 4.1 Introduction

This chapter outlines the findings from the study's specific objectives. It includes the identification and analysis of requirements, outcomes of model development, results from model deployment, validation of the developed mobile application, and a discussion of the findings, along with a comparison to previous studies.

#### 4.2 Identified Requirements

##### 4.2.1 Data Collection Results

In this project, the dataset includes three categories of cervical cancer: Grade One, Grade Two, and Grade Three, classified by pathology experts as explained in Chapter 3.5.1. Images for the "Not Cervical Cancer" category were sourced from Google. Table 1 shows the total number of images gathered from pathology experts in Arusha and Google.

The project required cervical cancer images, collected using a Samsung smartphone camera with the assistance of experts from SoftMed (T) Limited in Arusha. All datasets were stored in Google Drive.

**Table 1: Images Collected from Arusha and Google**

<b>Class of Cancer</b>	<b>Image collected</b>
Grade One	464
Grade Two	477
Grade Three	474
Not Cancer	461

##### 4.2.2 Augmented Dataset Results

The dataset was collected from the Arusha region with help from pathology experts and also included images from Google. After adding more images through data augmentation, the dataset grew to 2276 images across 4 classes. The images were then split, with 80% used for training and 20% for validation in each class.

**Table 2: Dataset after Augmentation**

<b>Class of Cancer</b>	<b>Image collected</b>
Grade One	564
Grade Two	577
Grade Three	574
Not Cancer	561

### **4.3 Requirement Analysis**

This section discusses the services provided by the mobile application. The specific objective was to develop a deep-learning model to enhance the detection of cervical cancer.

#### **4.3.1 Functional Requirement**

There are several functional needs involved in developing a deep learning model for enhancing cervical cancer detection in a mobile application, from data collection to model deployment. The following are the main functional requirements for the project:

**Table 3: Functional Requirement**

<b>Functional Requirement</b>	<b>Description</b>
Capture an Image	The application should support capturing images using various cameras (e.g., digital microscopes, smartphone cameras) and send it to the cropping page.
Crop the image	The application should crop the image to eliminate any unnecessary parts from the captured image and enable users to upload the image.
Upload an Image	The application should provide an easy-to-use interface for uploading cervical cancer images from the phone's gallery or capturing images directly from the camera after being cropped.
Display the Image	The application should allow users to display the captured or uploaded images of cervical cancer on the mobile screen
Model Runs	The application should prepare uploaded images by resizing and normalizing them, then run the CNN model to detect signs of cervical cancer, providing results quickly (within seconds)
View Detection Results	The application should display detection results (grade 1, grade 2, grade 3 or not cancer), including the diagnosis and confidence levels, and should be easy to navigate
More Information	The app should let the user view more details about the specific image after it goes through diagnosis.

### **4.3.2 Non-Functional Requirement**

Non-functional requirements define the criteria used to evaluate the system's performance. The efficiency and reliability of the system contribute to its overall effectiveness. Below are the identified non-functional requirements for the mobile application.

**Table 4: Non-Functional Requirement**

<b>Non-Functional Requirement</b>	<b>Description</b>
Availability	The application should be available at all times for pathologists to use.
Performance	The application should deliver diagnostic results quickly (within seconds) without slowing down
Usability	The user interface should be simple, requiring minimal training for cervical cancer professionals to use it effectively.

#### 4.4 Model Development Results

Deep learning models were developed to diagnose cervical cancer and assess their performance. The models were trained in two phases: initially using a CNN built from scratch, followed by a pre-trained model including VGG19, ResNet50 and MobileNet.

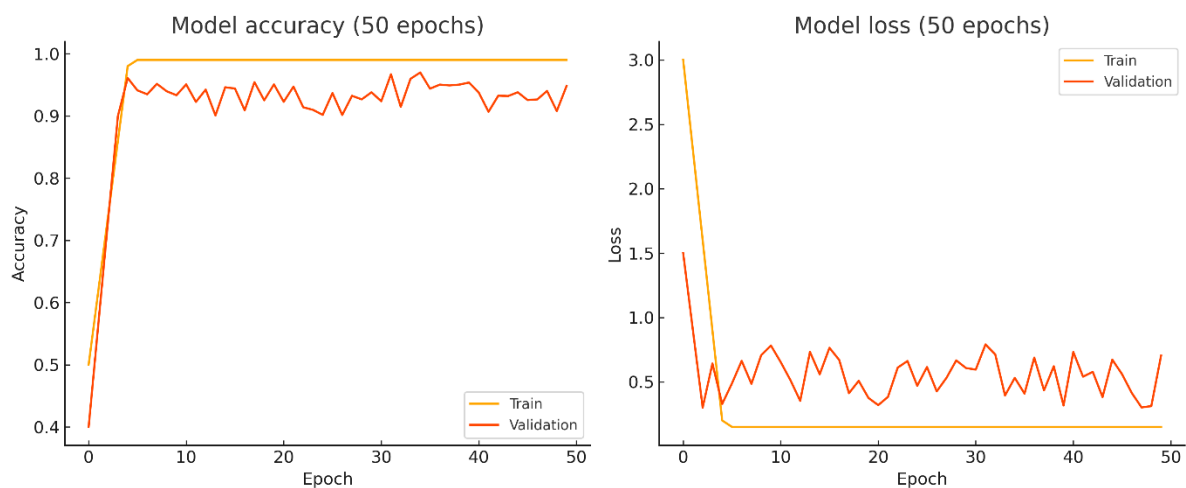
The CNN model, trained for 50 epochs, achieved an accuracy of 94% and a validation accuracy of 82%. Its loss value was 5.00%, while validation loss was 52.00%. The VGG19 model, trained for 50 epochs, achieved an accuracy of 97%, with a validation accuracy of 85% and a loss value of 3.5%, with validation loss at 48%. The ResNet50 model, trained for 50 epochs achieved an accuracy of 98.5% and a validation accuracy of 87%, with loss values of 2.5% and a validation loss of 45%. Lastly, the MobileNet model, trained for 50 epochs, achieved the highest accuracy of 99.59% and a validation accuracy of 89.6%, with loss values of 1.76% and a validation loss of 40.24%. Table 4 summarizes the model development results.

**Table 5: Model Performance Results**

<b>Model</b>	<b>Accuracy</b>	<b>Validation Accuracy</b>	<b>Loss</b>	<b>Validation Loss</b>
MobileNet	99.59%	89.6%	1.76%	40.24%
ResNet50	98.50%	87%	2.5%	45%
VGG19	97%	85%	3.5%	48%
CNN	94%	82%	5.00%	52%

#### 4.4.1 Selecting the Best Performing Model for Deployment

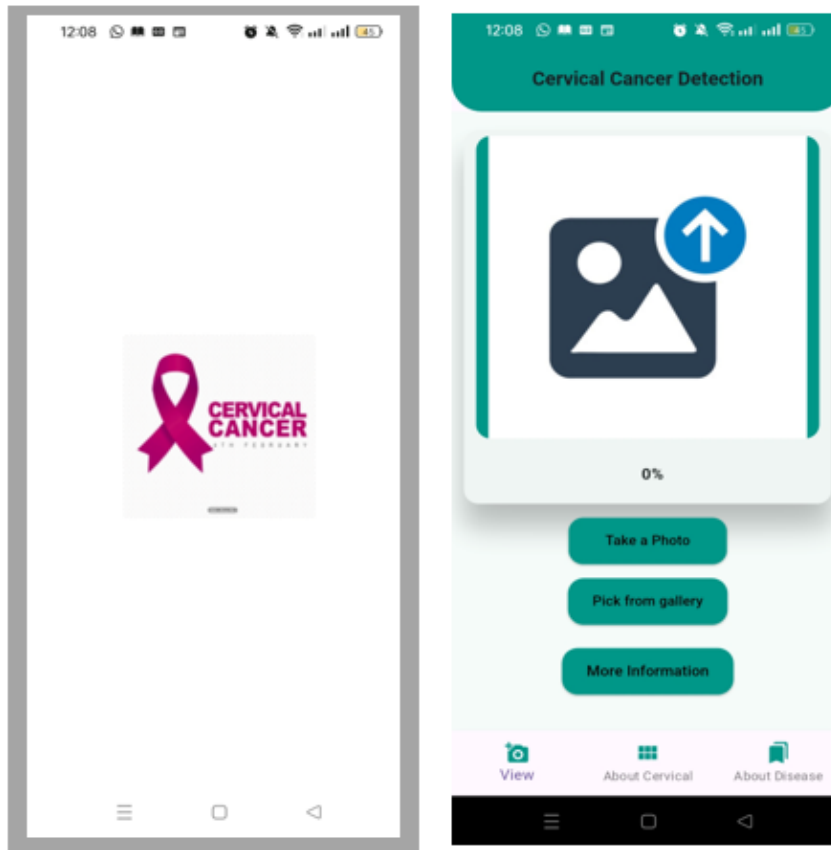
After reviewing the model performance results in Table 4, the MobileNet model was chosen for my mobile application due to its high accuracy of 99.59% and a validation accuracy of 89.6%, indicating strong performance on new data. It has a low loss of 1.76% and a validation loss of 40.24%, suggesting it makes accurate predictions and minimizes errors. MobileNet is specifically designed for mobile devices, making it lightweight and fast, ideal for applications with limited clinical expertise. Its efficiency enables quick deployment and real-time feedback, which is crucial for diagnosing cervical cancer. By balancing accuracy and efficiency, MobileNet becomes an excellent choice for this purpose.



**Figure 14: Training and Validation Accuracy and Loss for Mobilenet Model**

#### 4.5 Model Deployment Results

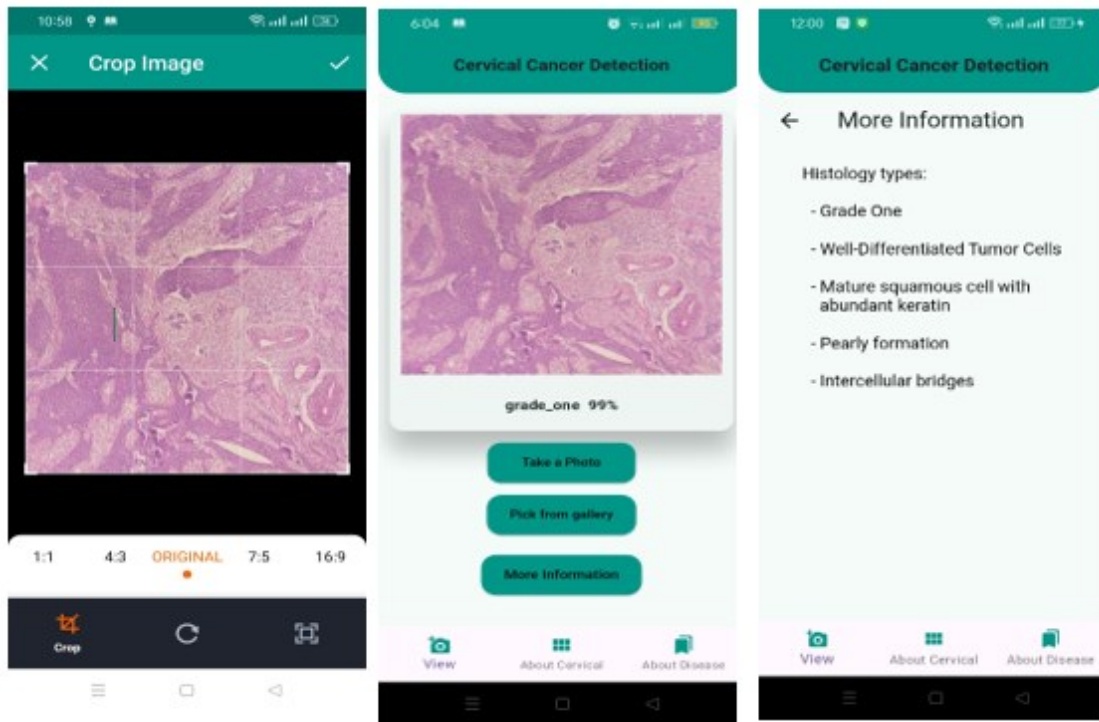
An intuitive and interactive mobile application was created to efficiently implement the MobileNet model.



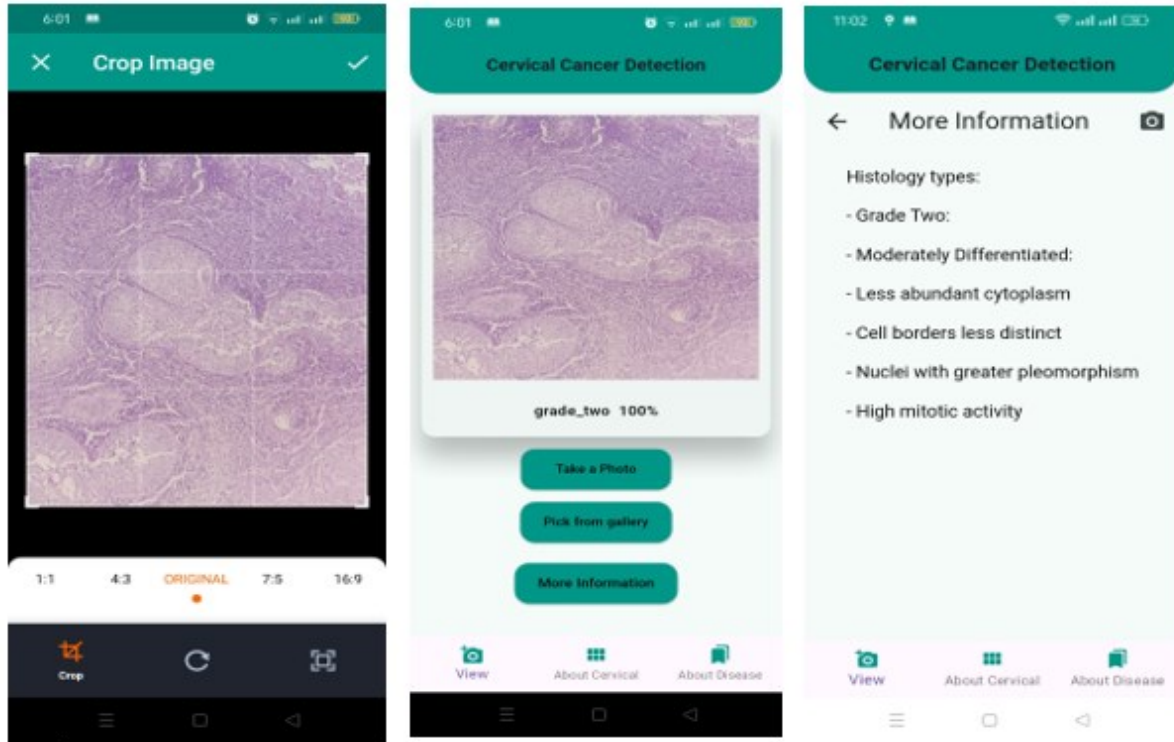
**Figure 15: Splash Screen and Detection Page of the Cervical Cancer Detection App**

A user-friendly and interactive mobile application was developed to assist pathologists in diagnosing cervical cancer. When the application starts, it shows a screen with the cervical cancer logo for a few seconds, then opens the detection screen (Fig. 15). On this page, the user can either take a photo using the mobile phone camera or pick an image from the phone's gallery for detection. After the cervical cancer image is captured or uploaded, a crop screen appears, allowing the pathologist to crop and remove any unwanted parts or background elements. The application processes the image in the background automatically and presents the detection results, indicating whether the image corresponds to cancer grade one, grade two, or grade three, along with a confidence score. If the uploaded or captured image is not of cervical cancer, the result indicates that it is not cancer, also with a confidence score. Displaying a confidence score in a mobile application adds valuable context and improves the reliability of predictions from cervical cancer or not cervical cancer detection model. When the pathologist presses the "More Information" button, they are taken to a page with detailed information about the specific cancer diagnosis identified in the image. Refer to Figs. 16, 17, 18, and 19 for more details. After reviewing more information for a specific image, the pathologist can press the back arrow at the top to return to the previous detection page and

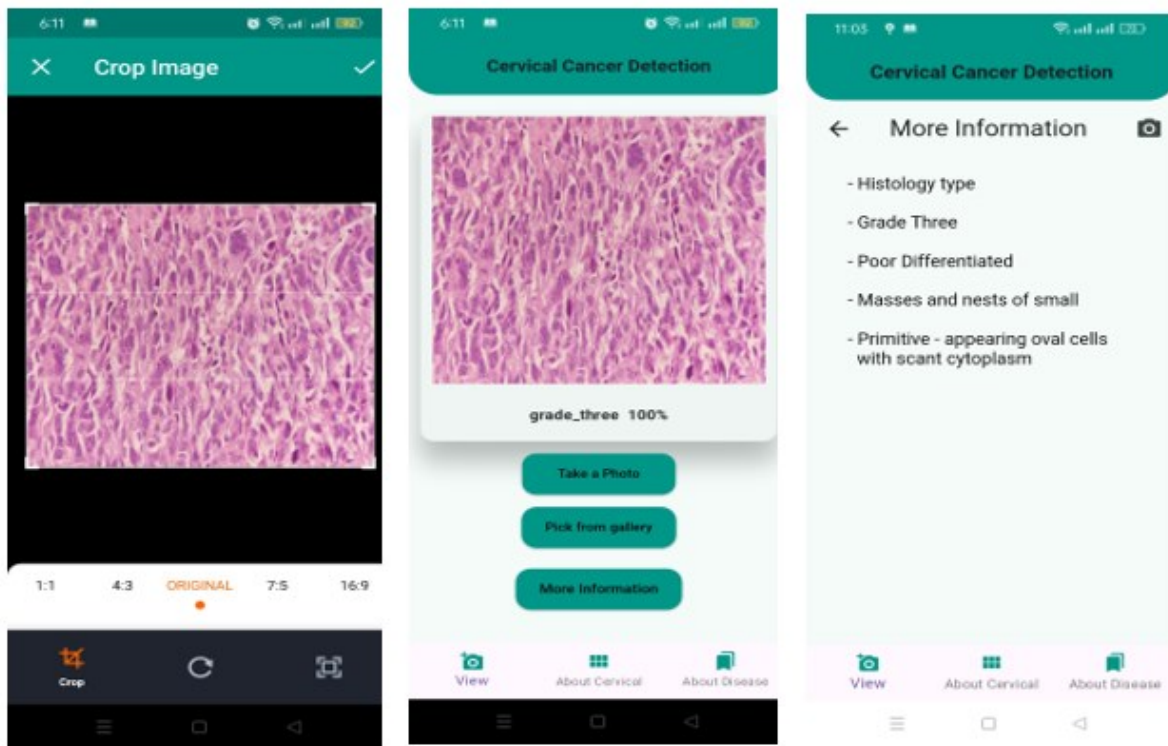
either capture or upload another cervical cancer image. The pathologist can also press the 'About Cervical' button to view detailed information about cervical cancer, and can also press the 'About Disease' button, they can see images of different stages or grades of cervical cancer, with explanations for each grade. Refer to Figs. 20 and 21.



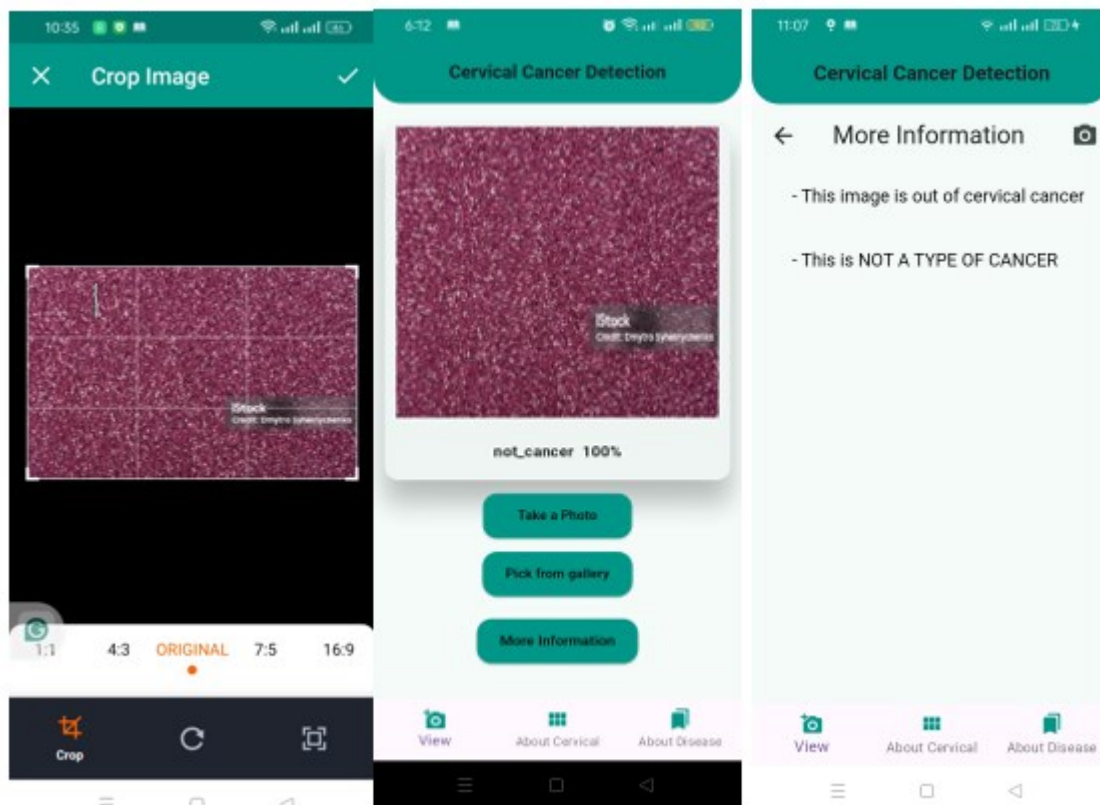
**Figure 16: Grade 1 Detection Page Showing Cropped Image, Results, and Disease Information**



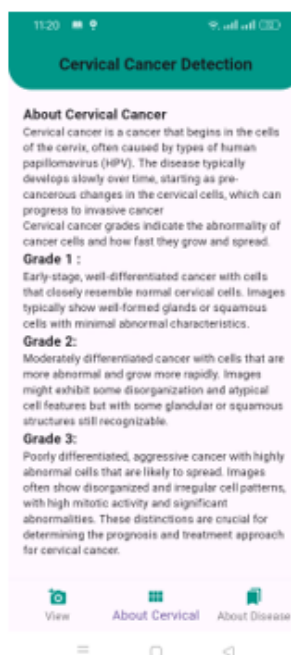
**Figure 17: Grade 2 Detection Page Showing Cropped Image, Results, and Disease Information**



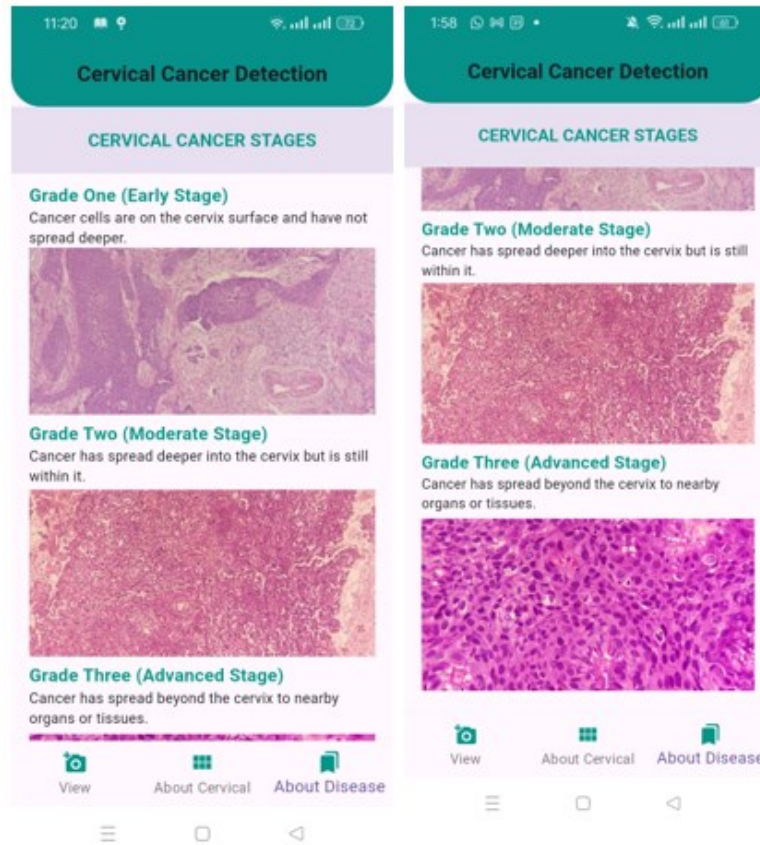
**Figure 18: Grade 3 Detection Page Showing Cropped Image, Results, and Disease Information**



**Figure 19: Not Cervical Cancer Detection Page Showing Cropped Image, Results, and Disease Information**



**Figure 20: Mobile Application Page Displaying the Explanation About Cervical Cancer**

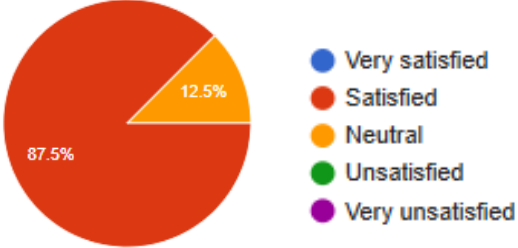
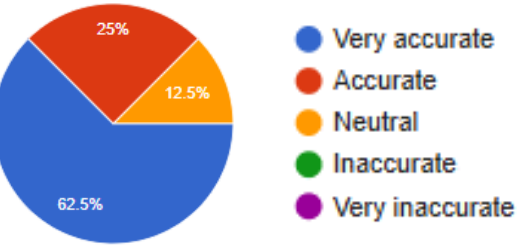
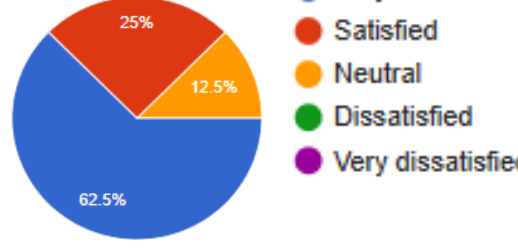
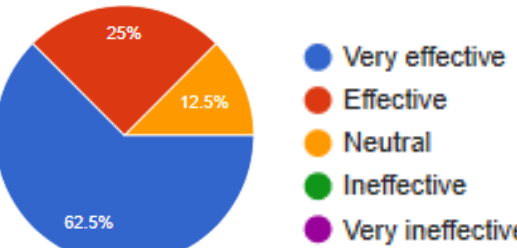
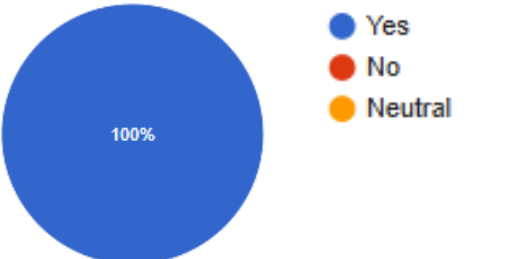
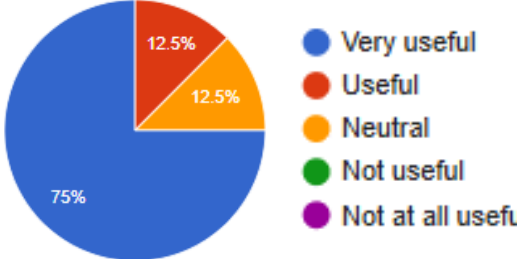


**Figure 21: Mobile Application Page Displaying the Stages of Cervical Cancer Disease**

#### 4.6 Validation of the Developed Mobile Application Results

Table 6 presents the validation outcomes of the cervical cancer mobile application.

**Table 6: The Results of the Mobile Application for Cervical Cancer**

<p>The prediction results were presented clearly</p>  <ul style="list-style-type: none"> <li>● Very satisfied</li> <li>● Satisfied</li> <li>● Neutral</li> <li>● Unsatisfied</li> <li>● Very unsatisfied</li> </ul>	<p>The app's predictions were accurate based on the diagnosis</p>  <ul style="list-style-type: none"> <li>● Very accurate</li> <li>● Accurate</li> <li>● Neutral</li> <li>● Inaccurate</li> <li>● Very inaccurate</li> </ul>
<p>Satisfied with the overall design layout</p>  <ul style="list-style-type: none"> <li>● Very satisfied</li> <li>● Satisfied</li> <li>● Neutral</li> <li>● Dissatisfied</li> <li>● Very dissatisfied</li> </ul>	<p>The app's image capture or upload was effective.</p>  <ul style="list-style-type: none"> <li>● Very effective</li> <li>● Effective</li> <li>● Neutral</li> <li>● Ineffective</li> <li>● Very ineffective</li> </ul>
<p>The speed of analysis and prediction was reasonable</p>  <ul style="list-style-type: none"> <li>● Yes</li> <li>● No</li> <li>● Neutral</li> </ul>	<p>More information section was useful and relevant for the prediction</p>  <ul style="list-style-type: none"> <li>● Very useful</li> <li>● Useful</li> <li>● Neutral</li> <li>● Not useful</li> <li>● Not at all useful</li> </ul>

#### 4.7 Discussion

The effectiveness of deep learning models in facilitating cervical cancer detection relies on models like CNN, VGG19, ResNet50, and MobileNet. Each of these models has its strengths and weaknesses, but MobileNet was specifically chosen for my mobile application due to its high accuracy of 99.59% and a validation accuracy of 89.6%, indicating strong performance on new data. This high level of accuracy is essential in medical applications, where reliable predictions can significantly impact patient outcomes.

MobileNet also has a low loss of 1.76% and a validation loss of 40.24%, suggesting that it makes accurate predictions and minimizes errors. The model was designed for mobile devices,

making it lightweight and fast, which was crucial for applications that need to operate efficiently on devices with limited clinical expertise, such as smartphones and tablets. Its efficiency allows for quick deployment and feedback, which is vital for diagnosing cervical cancer on time.

After the model was deployed to users, most reported that the app's predictions were either "very accurate" or "accurate," with no one choosing "inaccurate" or "very inaccurate." This shows that users trust the app's ability to provide reliable results, which is critical in the context of healthcare where accuracy can affect treatment decisions.

While CNN, VGG19, and ResNet50 performed better during some training phases, they had higher error rates and required more computational resources. These models may not be suitable for mobile deployment due to their size and complexity, which can lead to slower response times and a less efficient user experience.

The positive feedback from users regarding the app's navigation, predictions, and overall performance indicates that it is both easy to use and effective. The intuitive interface enhances user experience, allowing healthcare professionals to quickly interpret results without extensive training. The lack of negative comments further highlights the app's success in delivering accurate results and providing a smooth user experience.

MobileNet's high performance, efficiency, and ease of use make it an ideal option for mobile applications designed to detect cervical cancer. This project demonstrates the valuable role of deep learning in healthcare and emphasizes the importance of selecting a suitable model for mobile deployment. Such decisions can enhance patient care and lead to improved health outcomes. Future developments could aim to boost the model's accuracy by incorporating more diverse training datasets or experimenting with alternative models, all while maintaining the app's simplicity and responsiveness.

## CHAPTER FIVE

### CONCLUSION AND RECOMMENDATIONS

#### 5.1 Conclusion

The deep learning-based system for detecting cervical cancer offers promising capabilities for early diagnosis and timely treatment. By leveraging advanced models like CNN, MobileNet, ResNet, and VGG19, the system can accurately distinguish between various stages of cervical cancer and healthy tissue, enabling quicker and more efficient medical response. It effectively classifies images into categories such as grade one, grade two, grade three, or “not cancer.” MobileNet was chosen for its superior accuracy and performance, making the system more efficient overall. This approach helps reduce human error and supports healthcare professionals in making better-informed decisions. The mobile version enhances accessibility and is particularly useful in regions with limited medical expertise. Pathology professionals who have tested the system report it to be user-friendly and easy to navigate. Overall, this technology has the potential to greatly enhance cervical cancer detection and contribute to improved patient outcomes while lowering death rates related to the disease.

#### 5.2 Recommendations

##### 5.2.1 Recommendation for implementation

To make the mobile app effective for detecting cervical cancer, collecting high-quality images will be emphasized to improve accuracy and reduce bias. Regular updates with new data will be suggested to keep the model accurate. The model will be optimized for mobile devices to improve performance, while a simple, user-friendly design will be created to make the app easy to use. Working with pathology healthcare professionals will help ensure the model performs well, and educating users will clarify that the app will be a supportive tool, not a final diagnosis. Further projects on deep learning for medical imaging, multi-language options, and collaborating with health organizations will help more people access and trust the app, making it a valuable part of cancer detection in public health programs.

##### 5.2.2 Feature Work

The app can be improved by adding more diverse, high-quality images to make the model more accurate and secured. Investigating various deep learning models and combining the into a

single model to achieve better accuracy. It should have quality dataset tools for accurate results and a simple, clear design for both healthcare workers and patients. It should have two parts: one with detailed medical info for healthcare professionals and another with simple cancer prevention tips for users. Connecting the app to electronic health records (EHR) could help share patient data easily. Regular updates to the model will ensure it stays accurate, and multiple languages that make it accessible to more people. Gathering user feedback will help improve the app over time. The app could also expand to detect other types of cancer and work with health organizations to reach more people, especially in underserved areas.

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## APPENDICES

### Appendix 1: Interview Questions

- (i) Can you walk me through the steps you follow when diagnosing cervical cancer?
- (ii) What tools or equipment do you currently use for diagnosis?
- (iii) What are the biggest challenges you face when diagnosing cervical cancer?
- (iv) What factors contribute to delays in the diagnostic process?
- (v) Would access to an automated deep learning-based diagnostic tool improve your workflow?
- (vi) Do you think an automated system could complement the skills of pathologists?
- (vii) Do you think improving the diagnostic process could lead to earlier or more accurate detection?

## **Appendix 2: Validation Questionnaire for the Developed Mobile Application**

1. How satisfied were you with the overall design and layout?
2. Was the speed of analysis and prediction reasonable for you?
3. Did you find the app's predictions accurate based on diagnosis?
4. Were the prediction results presented clearly?
5. How effective was the app's image capture or upload function?
6. How useful and relevant was the information provided in the "More Information" section for understanding the prediction results?



# POSTER

## DEVELOPMENT OF A MOBILE APPLICATION FOR DETECTING CERVICAL CANCER USING DEEP LEARNING MODEL

Dorcas Kiswaga, Dr. Bonny Mgawe, Dr. Judith Leo



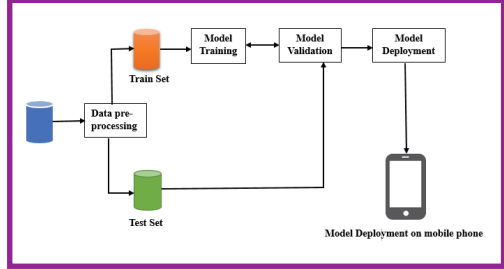
### Background of the Problem

Cervical cancer is a major health issue in low-income countries like Tanzania due to limited screening and late diagnosis. Traditional methods like Pap smear need experts and are often inaccessible. This project uses deep learning in a mobile app to enable early, automatic detection, helping improve diagnosis and reduce deaths in resource-limited areas

### Methodology

This project develops a mobile app that uses a deep learning model to accurately detect cervical cancer from medical images. The model, built with TensorFlow and Keras, was trained and tested using Google Colab with Python 3, then converted to TensorFlow Lite for deployment on an Android app developed in Visual Studio Code.

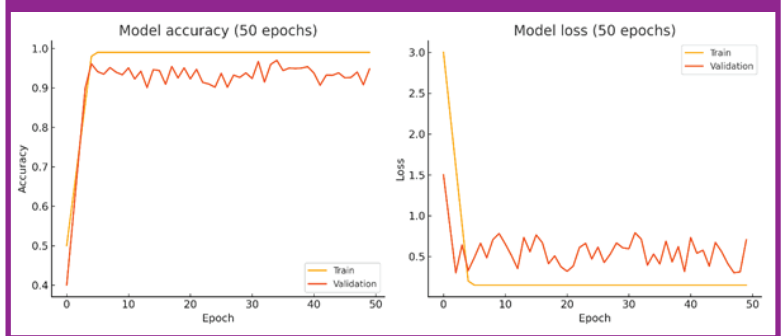
### Mobile Application System Design



### Models training

Model	Accuracy	Validation Accuracy	Loss	Validation Loss
MobileNet	99.59%	89.6%	1.76%	40.24%
ResNet50	98.50%	87%	2.5%	45%
VGG19	97%	85%	3.5%	48%
CNN	94%	82%	5.00%	52%

### Training and Validation Accuracy and Loss for Mobilenet Model



### Model Deployment Results

The application interface includes a main page for image upload, a cropping tool, and a detection screen that displays the detected grade (e.g., Grade 1, 99%) and provides detailed histology information. The 'About Cervical Cancer' section explains the stages of the disease:

- Grade One (Early Stage):** Cancer cells are on the cervix surface and have not spread deeper.
- Grade Two (Moderate Stage):** Cancer has spread deeper into the cervix but is still within it.
- Grade Three (Advanced Stage):** Cancer has spread beyond the cervix to nearby organs or tissues.