A Hybrid Approach for Cervical Cancer Classification: Combining D-CNNs, Transfer Learning, and Ensemble Models

By
Abu Hanzala
211-15-4022

Tanjila Akter
213-15-4334

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the **Degree of Bachelor of Science in Computer Science and Engineering**

Supervised by

Md. Sadekur Rahman
Assistant Professor
Department of Computer Science and Engineering Daffodil International University

Co-Supervised by

Dr. Md. Taimur Ahad
Associate Professor
Department of Computer Science and Engineering Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY
Dhaka, Bangladesh
September, 2025

APPROVAL

This Project titled "**A Hybrid Approach for Cervical Cancer Detection: Combining D-CNN, Transfer Learning, and Ensemble Models**" submitted by **Abu Hanzala** and **Tanjila Akter** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **09-04-2025**.

BOARD OF EXAMINERS

Dr. S.M Aminul Haque — **Board Chairman**
Professor & Associate Head
Chairman, Department of CSE, FSIT
Daffodil International University

Dr. Md Alamgir Kabir — **Internal Examiner 1**
Assistant Professor
Department of CSE, FSIT
Daffodil International University

Mr. Md Assaduzzaman — **Internal Examiner 2**
Assistant Professor
Department of CSE, FSIT
Daffodil International University

Dr. Md. Zulfiker Mahmud — **External Examiner**
Professor, External Member
Department of Computer Science and Engineering
Jagannath University

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Md. Sadekur Rahman, Assistant Professor,** Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Sadek 15.9.25

Md. Sadekur Rahman
Assistant Professor
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised by:

for Sadek 15.9.25

Dr. Md. Taimur Ahad
Associate Professor
Department of Computer Science and Engineering
Daffodil International University

Submitted by:

Hanzala 16.9.25

Abu Hanzala
Student ID: 211-15-4022
Department of Computer Science and Engineering
Daffodil International University

Tanjila 16.09.25

Tanjila Akter
Student ID: 213-15-4334
Department of Computer Science and Engineering
Daffodil International University

ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has assisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the **Final Year Design Project (FYDP)** successfully.

We are grateful and wish our profound indebtedness to **Md. Sadekur Rahman**, **Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of **Medical Imaging, Deep Learning in Healthcare, Disease Classification, Computer Vision** to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to the **Dr Sheak Rashed Haider Noori, Professor & Head** of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

Cervical cancer is the top cause of cancer deaths in women globally, despite being easily preventable through early diagnosis and treatment. This papers suggested deep learning methods, particularly transfer learnings, deep convolutional neural network (D-CNN), and ensemble learnings for automating the detection and classification of cervical cancer. In particular, we assess the effectiveness of four deep convolutional neural network structures: AlexNet, ZfNet, HighwayNet, and LeNet-5, in addition to four transfer learning architectures: EfficientNetB1, ResNet151, MobileNetV3, and DenseNet211. The dataset underwent preprocessing from the start. To achieve this, we conducted error level analysis (ELA) on the dataset to confirm that no patterns were overlooked within each image. We additionally carried out augmentation on the dataset (resizing, rescaling, flipping, rotating, zooming, and contrasting). Enhanced diagnostic accuracy can be attained through deep learning applied to the multi-cancer dataset. Comparative analyses were carried out swiftly to explore the precision of these architectures. We introduce a new hybrid ensemble model, AZL, which integrates AlexNet, ZfNet, and LeNet-5 to address the limitations of each individual model based on performance comparisons. We evaluated all these models in an experimental setup. The results of our experiments indicate that the AZL ensemble model reached a classification accuracy of 99.92%, surpassing individual D-CNNs and transfer learning models in precision, recall, and F1-score. These results emphasize the efficacy of ensemble deep learning methods in enhancing cervical cancer diagnosis. The method we developed shows potential to assist pathologists in diagnosing this disease promptly, particularly considering the limited resources available. In the end, it can precisely.

Table of Contents

List of Figures

List of Tables

Chapter 1
Introduction

This part gives a short summary of the project. It covers the background and main goals of the study.

1.1 Introduction

Cervical cancer affects many women around the world. It strikes more often in low- and middle-income nations [1]. Cases will likely rise a lot in the years ahead. Human papillomavirus, or HPV, causes most of these cancers [2]. Vaccines and early checks can stop HPV. Yet it still leads to the most cancer deaths in women globally [1]. The illness moves through steps. It starts with HPV infection, then forms precancer spots, and ends as full cancer [3]. Early on, no signs show up. It grows into cancer later. Screening helps catch and treat it [4]. Today, tests make spotting cervical cancer simple. Common ones include the Pap test for cells, vinegar wash called VIA, and HPV checks [5]. Still, setting up good screening faces big hurdles from high costs and poor setups [6]. In the past, this made care hard for women with the disease. Treatment varies by area and brings tough issues [7]. New studies test better ways to fight it. They aim to cut its worldwide harm and improve scans for early finds.

Three key methods transfers learing, D-CNNs, and hybrid learing stand out detection for cervical cancer. Transfers leaning serves as key tool in health image comparative for spotting cervical cell cancer. This holds true eventually with labeled data sets [8]. Such models need vast amounts of data for strong results. In health care, gathering this data proves tough, slow, and costly [9]. Transfer learning fixes this by applying past knowledge to boost model results on small data sets [10]. It draws on pre-trained models from large sets like ImageNet, which aids cervical cancer detection [11]. These models pick up image traits from earlier work that help new tasks [12]. Fine-tuning adapts the model to cervical cancer traits, leading to solid performance on limited data [13]. Studies show transfer learning excels at finding cervical cancer and cuts time to reliable results [14-15]. Researchers apply it with various CNN setups [16]. When applied, transfer learning highlights weak spots in target data sets by fine-tuning the base model [17].

D-CNNs, made big impact for medicine for spotting cervical cancer in images [8]. These networks sort out image details with ease using their stacked layers of filters [18]. Every pattern from the outermost layer to the innermost layer plays a crucial role in identifying cervical cell cancer [19]. D-CNNs can be trained to examine different kinds of diseases, allowing for the easy detection of cancerous cells and other ailments [9]. Extracting image features with the D-CNNs model from extensive datasets can be labor-intensive [18]. Numerous studies have demonstrated that D-CNNs can effectively identify cervical cell cancer, allowing pathologists to depend on these instruments [14] [20]. So, experts apply transfer learning to boost D-CNNs model results [13].

Ensemble learning stands out as a strong way to spot cervical cancer and similar illnesses [21]. It blends multiple models into one strong base that predicts far better [22]. These base spots every image detail. That cuts down mistakes a lot [23]. You can build an ensemble by mixing D-CNN and transfer learning for cancer checks [24]. Teams use methods like bagging, boosting, and stacking to make these models [25]. Bagging averages outputs from many base models. Boosting trains the base step by step. It fixes errors as they pop up. Stacking, though, joins predictions from several bases. A meta-learner then trains them as a group [26].

Transfer learning, D-CNNs, and ensembles learning techniques can effectively detect cancerous cells in cervical cell cancer diagnosis by leveraging the characteristics of these model [8]. Deep CNN architectures are capable of capturing intricate elements of an image, exceeding the abilities of machine learning techniques that depend on manually crafted features [18]. Nevertheless, developing models from the beginning necessitates a significant volume of labeled data, which poses a challenge in the medical field [15]. Transfers learing proves to be essential when utilizing a pre-trained model, as it can identify significant diseases such as cervical cancer even in limited datasets [10], [12]. It not only addresses the issue of data scarcity but also enhances it. It relies on the source dataset and target dataset of the transfers learing model. That is the reason it is required. If this isn't completed, then different kinds of issues may arise [17]. Numerous studies indicate that there are significant gaps in the literature regarding cervical cell cancer detection. D-CNNs can effortlessly recognize different patterns and textures from the early stages of diseases by using several filters [18]. D-CNNs addresses the issue of limited data by employing pre-trained boundaries from transfer learning. D-CNNs is capable of recognizing different patterns and textures from the early stages of diseases by utilizing various filter [13]. Conversely, Ensembles learing integrates multiple models to significantly enhance the effectiveness of D-CNNs and transfers learing [28]. Regardless, the primary issue with ensembles learing models is the computational expense linked to employing several model [26]. The performance of an ensembles models relies on the base models [29].

1.2 Motivation

Cervical cancer tops the list of cancers that strike women around the globe. It hits hardest in poorer and middle-income nations. There, routine checks and skilled lab reviews remain scarce. This disease can be stopped with early detection and care. Yet it often goes unnoticed until late stages. That happens from delays in action. Old ways to spot it take too much time. They depend on experts' personal views. This causes uneven outcomes. Lately, AI and deep learning have proven strong in scanning medical images. They offer quick, precise, and wide-reaching tools for diagnosis. Still, current models face issues like overfitting. They also struggle with broad use. Data sets prove complex, and classes sit out of balance. So no one deep learning tool shines in every case.

Driven by these challenges, this research seeks to enhance the precision and dependability of cervical cell cancer identification by assessing various deep convolutionals neurals network (D-CNN) models or architectures, also transfers learing frameworks. We also present an ensembles models (AZL) that merges the advantages of AlexNet, ZfNet, and LeNet-5 to address the limitations of each individual model and enhance overall classification accuracy. Additionally, by employing sophisticated preprocessing methods like error level analysis (ELA), This study uses data aogmentation methods ands large-scale image boosts to build a strong and precise tool for diagnosing cervical cancer. It helps doctors in places short on resources and works to cut down deaths from the disease.

1.3 Objectives

The overall goal is to develop one fast and reliable deep learing model this sorts out cervical cancer cases. Here are the key aims of the work:

1. Build and test deep learning models (AlexNet, ZfNet, HighwayNet, LeNet-5, EfficientNetB0, ResNet50, MobileNetV2, DenseNet201) for spotting and sorting cervical cancer on its own.
2. Check how well prep steps on the data work, like Error Level Analysis (ELA) and boosts such as resijing, reskling, fliping, rotasion, zoomiing, also contrsting, to raise model success.
3. Compare D-CNNs and transfers learing setups depends on accoracy, precisions, recal, and F1-scores.
4. Create and apply an ensembls models (AZL) that blends Alex-Net, Zf-Net, and LeNet5 fix weak spots in single models.
5. Gauge how the new AZL ensemble boosts accuracy and trust in finding cervical cancer over other methods.
6. Help lower death rates from cervical cancer with a solid, easy-to-scale AI tool for diagnosis.

1.4 Methodology

The methodology for developing a Deep learning system for classifying cervical cancer. involves a systematic approach to dataset, preprocessing, image augmentation, experimental setup, model selection, and model training and evaluation. Below are the key steps involved:

1. Dataset

    - This approach draws from the Multi Cancer Dataset [45]. That set holds 25,000 images spread over those same five classes: metaplastic, dyskeratotic, koilocytotic, parabasal, and superficial-intermediate.
    - Images resized from 512×512 to 224×224×3 for computation efficiency.
    - Data split: 64% train, 20% test, 16% validation.

2. Preprocessing

    - Applied Error Level Analysis (ELA) to enhance hidden patterns.
    - Scaled pixel values (0–1 normalization).

3. Image Augmentation

    - Data Augmentation Methods: Resizing images, rescaling them, flipping, rotating, zooming in or out, adjusting contrast, turning to grayscale, and normalizing values.

4. Experimental Setup

    - Activation Functions: ReLU, Softmax, and SELU.
    - Optimizers Used: Adam, Adagrad, and SGD.

- Learning Rates: 0.01, 0.001 and 0.0001.
- Loss Function: Categoricals_cross-entropy.
- Training Setup: 50 epochs with early stopping after 5 steps of no improvement.
- Batch Sizes: 8, 16 and 32.

5. Model Selection

- Transfer Learning Models: EfficientNetB1, MobileNetV3, DenseNet211, and ResNet150.
- Deep CNNs Architctures: Alex-Net, LeNet5, HighwaNet, and Zf-Net.
- Ensemble Approach (AZL): Merges Alex-Net, ZF-Net, and LeNet5 pump results.

6. Models Training and Evaluation

- Optimized parameters for best performance.
- Avoided overfitting with early stopping and batch size tuning.
- Evaluations Metric: Accurecy, precisions, recal, F1-scores, and losss.

1.5 Project Outcome

Researchers used deep learing frameworks there are transfers learing, D-CNNs, also ensembles learing. They built a system that detects cervical cancer well. The data set got better for strong model training. They applied fixes after processing, such as Error Level Analysis (ELA) and image changes. Multiple architectures including D-CNNs models (AlexNet, ZfNet, LeNet-5, and HighwayNet) and transfer learning models (ResNet50, EfficientNetB0 MobileNetV2, and DenseNet201) were evaluated comparatively. Tests prove the new AZL ensemble model scores the top accuracy. It beats single models precition, recal, and f1-scores. These findings show methods boosts diagnostic accuracy.

The developed system provides a reliable, cost-effective and scalable solution to assist pathologists in early and accurate cervical cancer detection, especially in limited healthcare settings. Ultimately, this result contributes to reducing diagnostic errors and enabling timely treatment, as well as reducing mortality rates.

1.6 Organization of the Report

This report aims to give a full grasp of the paper "Cervical Cancer Classification using Deep Learning Technique." It covers all parts, from the drive behind it to how it was built. Here is the paper's outline:

Chapter 1. Introduction: It sets the scene with background info, the main problem, reasons for the work, goals of the research, and a quick look at the planned method. The chapter also lists what results the study hopes to achieve.

Chapter 2. Background: This builds the base theory for the study. It includes a close review of past studies, key related projects, and an analysis of gaps that show why this research matters.

Chapter 3. Research Methodology: The section explains the chosen approach. It covers the data set, steps to clean the data, ways to boost images, the test setup, choice of models, training and checks for results, overall system build, job splits, and the full project timeline.

Chapter 4. Implementation and Results: Explains the implementation process, environment setup, and performance evaluation of different deep learning models. It also presents the experimental results and comparative analysis.

Chapter 5. Engineering Standards and Design Challenges: Discusses compliance with software and hardware standards, key challenges faced, and their impact on society, environment, and sustainability. Ethical considerations and sustainability aspects are also addressed.

Chapter 6. Conclusion: It sums up key findings. It points out limits. It offers ideas for next steps.

Chapter 2

Background

This chapter covers the key theories, past research, gaps in knowledge, and main points tied to the study.

2.1 Introduction

Cervical cancer ranks high among cancer deaths in women around the world. It can be stopped with early checks and quick care. Old ways to spot it rely on people's views and skilled doctors. This often slows down early finds. New tools in AI have changed that. Deep learning now shines in checking medical images. It gives fast, right answers without much human help.

This work uses group learning methods like D-CNNs, transfer learning, and ensemble learning. The goal is a system to find cervical cancer. These models prove deep learning boosts spot-on checks. They can aid doctors in catching it soon. In the end, this cuts deaths.

2.2 Literature Review

Cervical cancer poses a big health risk. It hits low- and middle-income countries hard. Shots against HPV and early tests can stop it. Yet many women face pain from lack of good care. Weak screening access blocks early spots. Tools like Pap tests, VIA, and HPV checks help find it. Still, high costs and poor setups stand in the way. Current studies work to better screens and cures. This eases the worldwide load of the cervical cell cancer.

2.2.1. Ensembles Depend Approache for Cervical Cell Cancer Classification

In [30], experts built an auto system for cervical cancer checks. They drew from number-based data. A voting setup mixed three ML models with CNN traits. It hit 99.99% right answers. In [31], the team fixed gaps in data for cancer checks. They used health records on cervical cancer. An ensemble voting tool joined three ML models. It scored 99.52% acc, 97.99% precition, 95% recal, and 96.90% F1 scores. In [32], a team made an ensemble transfer learning setup for cancer class. They took the Herlev data set. Transfer learning drove the cancer checks. It reached 97.38% accuracy.

2.2.2. Transfers Learing in Classing Cervical Cell Cancer

The writers [33] suggested a combined deep-learing model to enhance cervical cell cancer detection. The writer utilized a Cancer-multi Dataset to identify cervical cell cancer. The writer showcased featur extrction and dimensionaly reduction employing Desnet211 and InceptionV5. The model reached an accuracy of 97.57%. The researchers [34] utilized a transfers learing model to categorize cervical cell cancer. The writer utilized the Herlev and Sipkmed datasets for classifying cervical cell cancer. The writer utilized 17 pre-trained architectures. The model achieved 95.90% accuracy using ResNet121, 98.75% with VGG19, and 98.63% with DenseNet211. Researchers [35] created a model to sort cervix images for cervical cancer. They drew from a free Kaggle dataset. They built a deep learning setup with transfer learning. It hit 96.21% accuracy.

2.2.3. Machine Learning Methods for Prognosis and Diagnosis

Researcher [24] built a machine learning tool to forecast cervical cancer outcomes. They pulled data from a UCI ML repository. They applied a ML approach sort cervical cell cancer case. Researchers [36] made a machines learing tool to spotting cervical cell cancer on its own. They worked with cytology Paps smears image to diagnose cervical cell cancer multiple classes. They tested a SVM and a deeps Gaussians process. The support vector machine (SVM) scored 100% accuracy. The deep Gaussian process got 99.58%. Researchers [37] made a machines learing tool spot cervical cell cancer. They use a UCL datasets on cervical cell cancer risks. They picked a voting classifier. It scored from 93% accuracy. Researchers [38] shared a machines learing tool to classify cervical cell cancer. They use there own handmade datasets for the predictions. They tried decision trees, logistic regression, supprt vectors machine (SVM), RL, KNN, and XGBoost. One model reached 100% accuracy. The support vector machine got 99%. Researchers [39] built a machine learning tool to gauge chances of cervical cancer. They used the UCI dataset on cervical cancer risks. They tested logistics regressions, RF, decisions trees, and AdaBoosts. It reached 84.80% accuracys.

2.2.4. D-CNN in Cervical Cell Cancer

Cancer Researchers [40] suggested a deeps learing tool automate cervical cell cancer checks. The authors use a Pap smear image dataset to sort cases. They tested 28 deep learnig model for classification. These included CNNs, ViT for sorting. One models hit 98.58% accurcy. Researchers [41] offered a multi-class sorting models to cervical cell cancer. They used the Herlev and Sipkmed data. They built a ConvoNet with transfers learnig and progresive resizig and sorting. It scored 98.80% accuracys.

2.2.5. Hybrids Approache for classification

This models scored 98.21% accuracy sorting. Researchers [42] suggested a machin learing clasifier to find cervical cell cancer. They used a clinical data. They applied preprocesing steps pulls learn. It reached 99.16% for classification. Researchers [43] suggested a deeps learing to earlly spotting, sorting of cervical cell cancer. They used the SIPKMeD data. They added preprocessing, feature cuts, feature pulls and blends, plus sorting models. It hit 97% accuracy.

2.2.6. Segmentation Technique

The Researchers [44] suggested a deep learning model to segment medical operation volumes form MRI imaging in radiotherpy for cervical cell cancer. They use thier handmad cervical cancer data. They tested Attentions U-NetV2 and 2D U-NetV2 model. It scored 86% accuracys. Table 1 shows the comparison.

Table 2.1: Research Matrix for This Research

Authors	Year	Title	Methodology	Key Findings
Hybrid Depend Approache				
Munshy et al. [30]	2024	New method for group learning with SVMs-filled ADASYNY traits to boosts cervical cancer	Voting classifier, CNN-generated features	Automate Classification systems
Aljree et al. [31]	2024	Better forecasts for cervical cancer by using KNN filler and group model learning.	Hybrid classificaiton	Missing images in detention
Xue et al. [32]	2020	Use of shift learning and group learning for sorting cervical tissue images.	Ensembled Transfer Learning	Transfers Learning Models

Transfer Learning Based Approaches				
Sharma et al. [33]	2025	Boosting cervical cancer sorting with a mixed deep learning method that joins DenseNet201 and InceptionV3.	DenseNet201 and InceptionV3	Hybrids models for classifications
Kuar et al. [34]	2025	Side-by-side look at deep shift learing model to sorting cervicals cell cancers from Paps smaer pictures.	16 pre-trained CNN models	Transfer learning models using classification
Dhawan et al. [35]	2021	Sorting cervix images to predict cancer outlook with deep neural nets and shift learning.	Deep learning, transfer learning	Cervical cancers classification using deep learning
Machine Learning Based Approaches				
Uddin et all. [24]	2024	Group ML method to forecast cervicals cell cancer with mixed trait picking.	ML classifications	Real time prediction
Ahihakiye et al. [36]	2024	Fine-tuning cervical cancer sorting via shift learing and deeps Gussian processs, also SVM.	SVMs, Deep Gaussian Process model	Automate detect system
Alsmariy et al. [37]	2020	Predict Cervicals Cell Cancer using ML Method.	Voting classifier model	Diagnosis using ML
Al Mudwi et al. [38]	2022	Models for predict cervical cell cancer using ML architecture.	DT, SVM, RF	ML models used for prediction
Yin et al. [39]	2021	How machine learning helps predict cervical cancer.	Logitic regresstion, Random Forst, Decition Tree, AdaBoosts	Cervical cell Cancer classify
D-CNNs Based Approaches				
Pacals et al. [40]	2025	New deep learning model based on CNN and ViT for early skin cancer spotting	27 deep-learing model (DCNNs, ViT)	Automat cervicals cell cancers diagnosis
Bhatt et al. [41]	2021	Finding cervical cancer in full Pap smear slide images with ConvNet, shift learning, and step-by-step resizing	ConvNet, Transfer Learning, Progressive Resizing	Multiclass cervical cancer classification model
Hybrids and Featares Engineerings Approache				

Aly et al. [42]	2024	Group sorting method to cervicals cell cancers forecasts use to lifestyle progration factor	Preprocesing, and features extractions methods	Cervicals cell cancers classification
Ahamed et al. [43]	2024	Fastly spotting, grouping of cervicals cell cancers with smothing crossentopy multideeps shift learing	Features reducsion, extracsion and fusions	Early Detect of cervicals cell cancers
Segmented Approceshe				
Zabiholahy et al. [44]	2022	Full auto outlining of treatment area in cervical cancer from MRI scans using convolutional neural networks.	U-Nets, 2D U-Nets	Segmentation for radiotherapy

2.3 Gap Analysis

Despite advances in medical imaging, cervical cancer detection still relies on manual examination, which is prone to human error. This creates a gap in consistent and accurate diagnosis, particularly to the first stage of the illness. Although deeps learing and transfers learing architecutre had show fairly best accuracy in medical image classification, their application in cervical cancer detection has been limited. Most studies use either a single CNN or transfer learning model, resulting in poor performance and generalization. Also, while applying p-processing and augmentation methods in many tasks, they often ignore techniques such as Error Level Analysis, which can reveal hidden image patterns, and this leaves an opportunity to improve the input quality for learning better models.

One key gap lies in comparing various architectures. This issue hinders picking the top method in studies that test D-CNN models on the same dataset with transfer learning. On top of that, few hybrid ensemble methods appear in cervical cancer studies. This shortcoming limits near-perfect accuracy in diagnosis. Most current approaches stick to one architecture. They miss the added strength from combining several models.

2.4 Summary

Cervical cancer poses a major health threat worldwide. It hits hardest in areas short on medical care and clinics. Early spotting proves tough there. Old diagnosis tools often rely on human judgment, which can falter. They also demand high costs and solid setups. New tools show promise for better auto-detection. Deep learning stands out among them. Researchers have used deep convolutional neural networks and mixed models. These classify cancer from medical scans with strong results and speed. Among these models, ensemble and transfer learning hotels further improve performance by exploiting the complementary strengths of multiple architectures, which contribute to better model reliability by de-processing quantification and segmentation techniques. Overall, these methods show promise in timely and accurate cervical cancer diagnosis, potentially reducing mortality and improving patient outcomes.

Chapter 3

Research Methodology

This part covers methods, steps, also design choices used in the project. It keeps the work orderly, planned, and tied to the goals.

3.1 Methodology

3.1.1 Overview

In this phase, we built an auto-system for cervical cancer detection with deep learning. It begins with dataset prep. We gathered images of cervical cancer. Then we cleaned and improved them. Techniques included resizing, rescaling, cropping, rotating, zooming, and tweaking contrast. We ran error level checks to spot fine details in images. This part explains all these steps. It also covers choosing deep learning models that fit the study's aims. These models boost prediction strength and reliability. We trained them for cancer classification.

3.1.2 Proposed Methodology

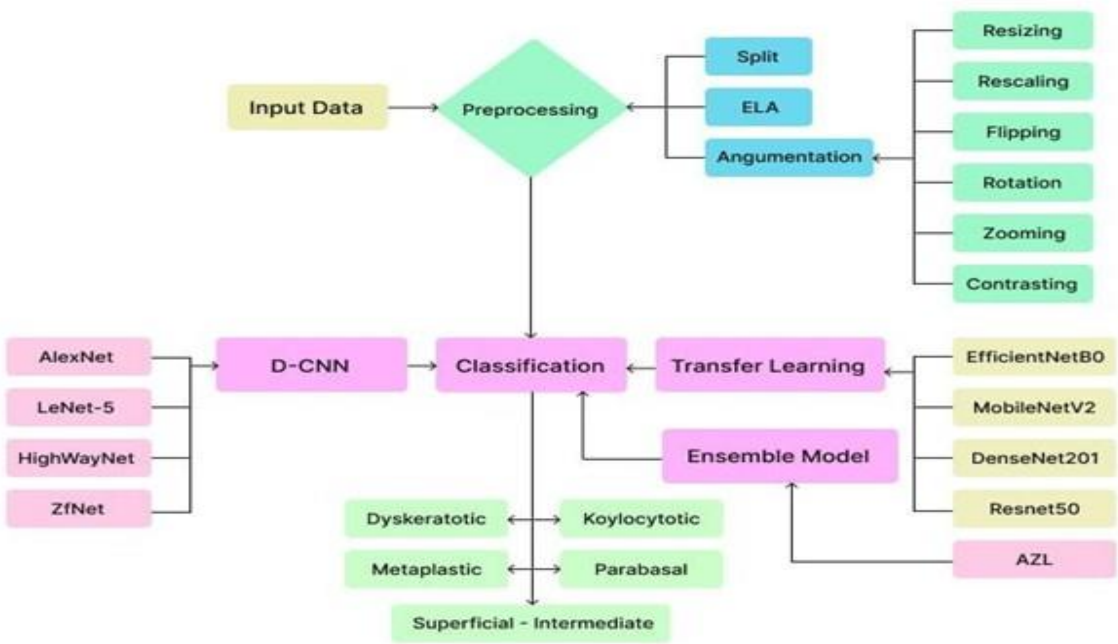


Figure 3.1: Proposed Methodology

3.1.3 Functionals and Nonfunctionals Requirement

- For funcsional needs, the system lets users upload images linked to cervical cancer. Images must be in standard formats. The system must display a preview of the uploaded image before submitting it to the system. After the image is uploaded, the system must pass the image into these models and return the predicted class. The system must clearly display the prediction in the output section. Users should be able to reset the input preview or prediction results. The system must notify users if an invalid file is uploaded.
- For non-functional requirements, predictions should be returned quickly, reducing user wait times. The overall interface should be simple and responsive across devices. The system should handle concurrent users and fail gracefully if the model server becomes unavailable. Only image files should be accepted, and user data should not be stored permanently. The system should support future integration with additional medical data. The code should also be modular and easy to update or extend.

3.1.4 Workflow Diagrams

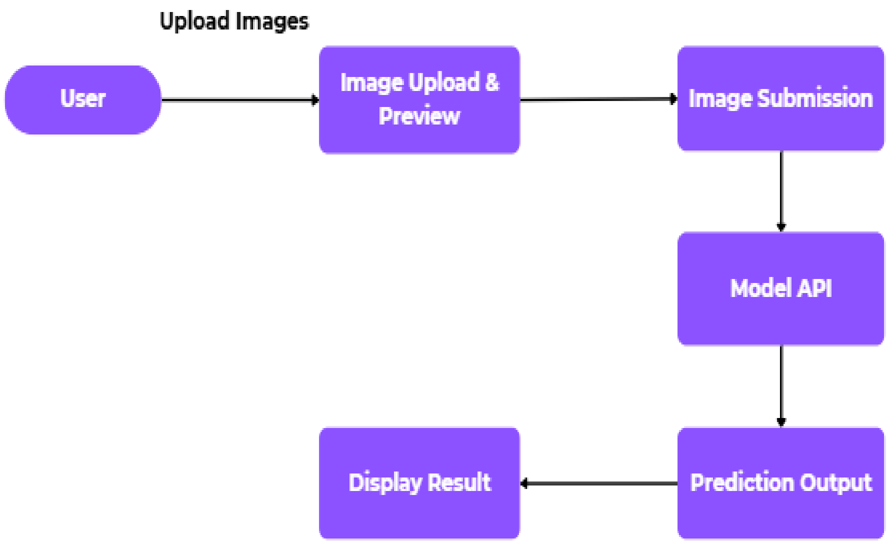
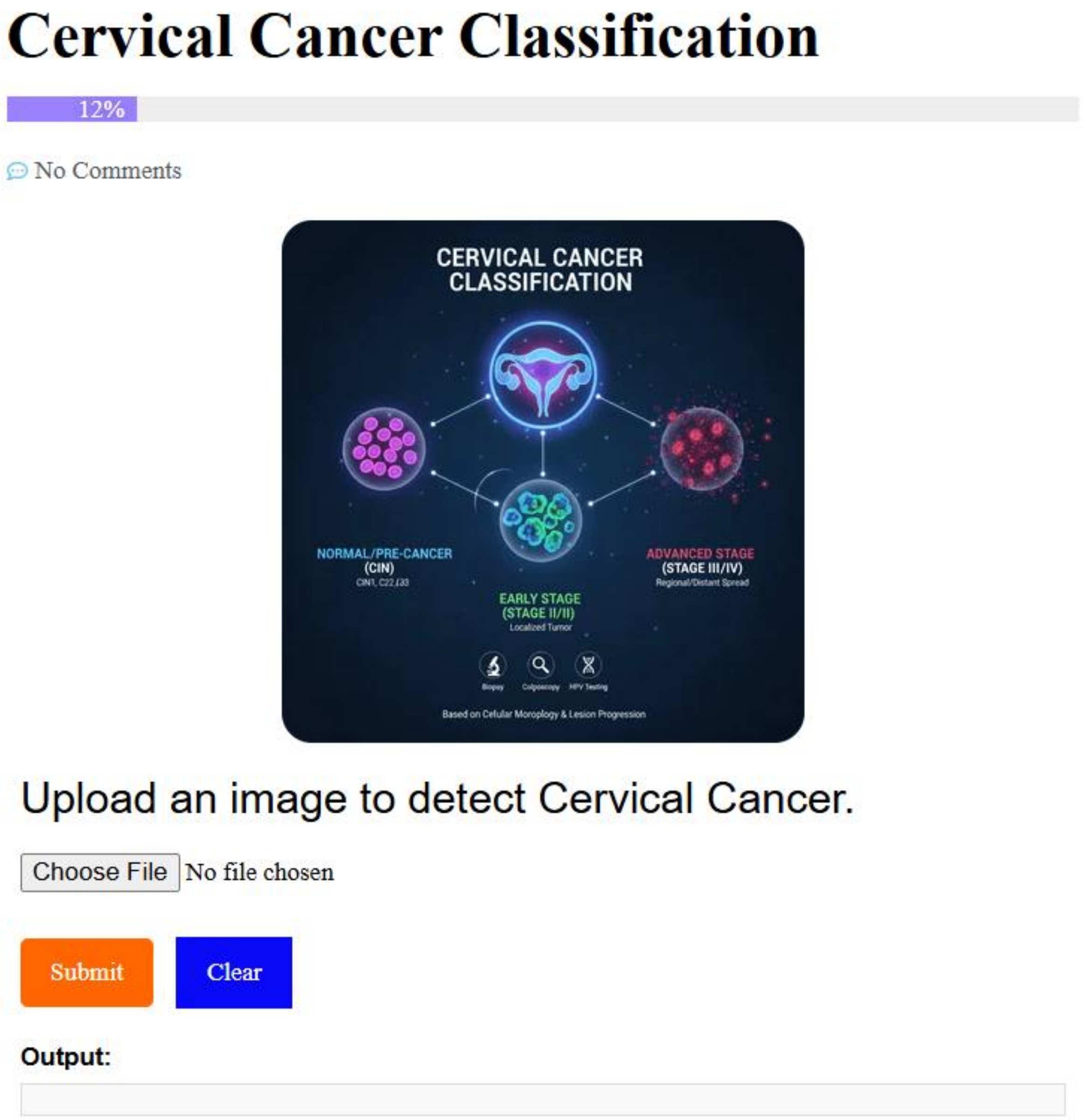


Figure 3.2: Systems Workflow

3.1.5 User Interface Designs



Figures 3.3: UI Design

3.2 Detailed Methodology and Design

3.2.1 Dataset

This study created a tool to spot cervical cancer early and assess it well. We used a image datast called "Multy Cancers Datasets" for testing [45]. The entire folder consist of total 25000 images that were divided into five categories: Metaplastic, Dyskeratotic, Koilocytotic, Parabasal, and Superficial-Intermediate. Each image had dimensions of 224 x 224. The model was divided into five classes for training, testing, and validation in the ratio of 64:16:20. The image of each class is shown in Figure 3.4.

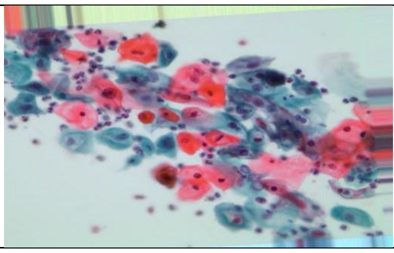
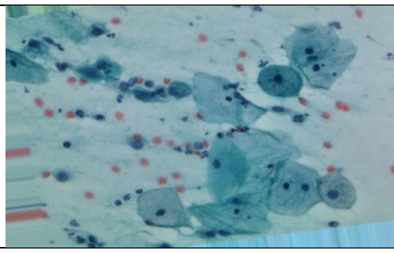
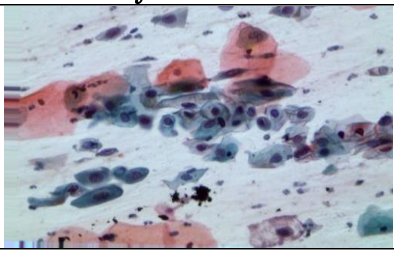
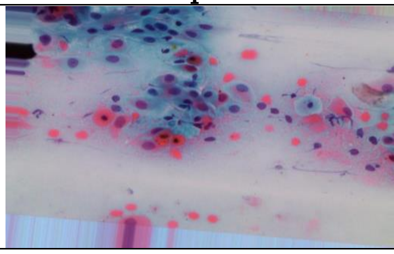
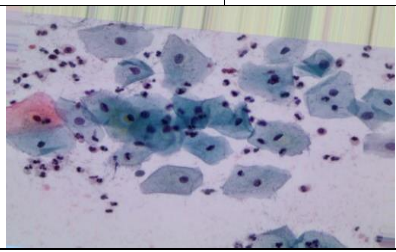
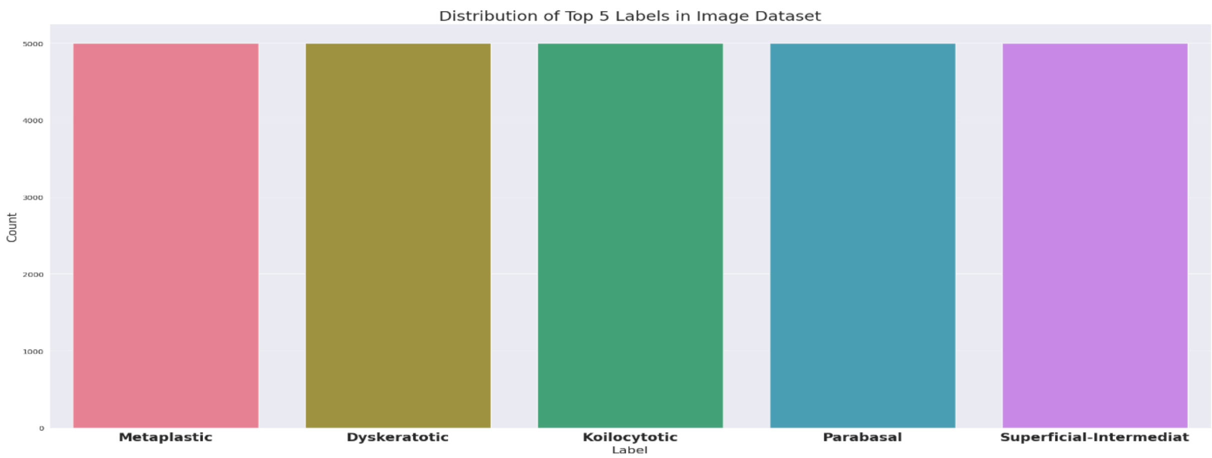
	
Dyskeratotic	Metaplastic
	
Koilocytotic	Parabasal
	
Superficial-Intermediate	

Figure 3.4: Sample of image used in the research for cervical cancer classification

3.2.2 Images Acquisision and Preprocesing

We drew from a folder to find cervicals cell cancers. It split fives groups: Metaplastics, Dyskeratotics, Koilocytotics, Parabasals, and Superficial-Intermediates. Each group held equal data amounts. Uneven data can trip up models. The images came pre-processed. We showed class counts a bar charts in Figures 3.5.



Figures 3.5: Every classes as a bar charts

We chose this model because it performed very well because all classes had equal amounts of data. We use a total of 25,000 images for this model. Each class had 5,000 images. We divide the dataset into three parts, which are train, test, and validation. For the train, For training, we used 16,000 images, or 64 percent of the dataset. The test set got 5,000 images, or 20 percent. Validation used 4,000 images, or 16 percent. Every image started at 512 by 512 pixels. We resized them to 224 by 224 pixels. This change boosted the model's speed. We shaped each class to 224 by 224 by 3. That cut down on compute time a lot.

To boost model performance, we applied Error Level Analysis, or ELA. ELA helps spot issues in image parts quickly. If a section is hard to detect, ELA flags it for review. It picks a random image from the data. Then it runs the image using OpenCVs. Next, it scale the small pixels value from 1 to 0. It compress the image step by step from the start. ELA finds differences between the original and the compressed version. This shows real mismatches clearly Figure 3.6.

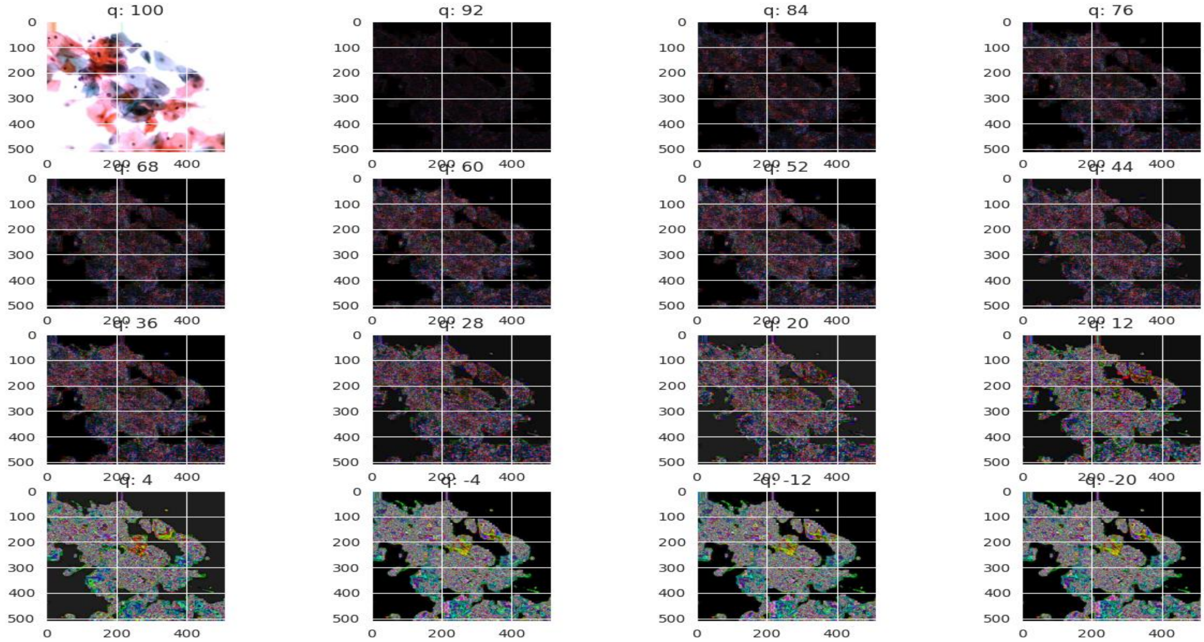
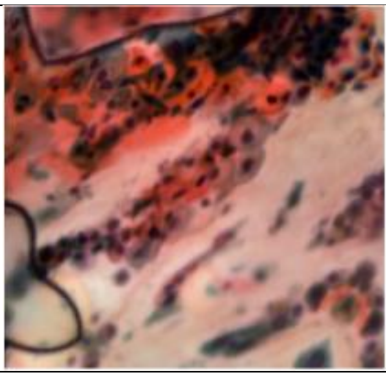
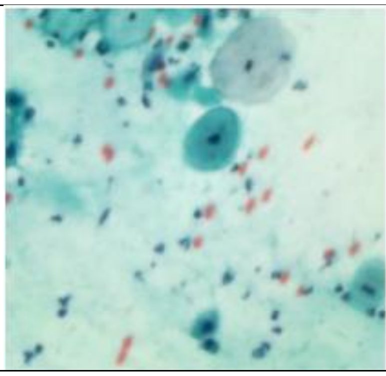


Figure 3.6: Errors Level Analysis of the images

3.2.3 Image Augmentations

We preprocessed images once more. We turned them to grayscale, set uniform sizes, and normalized pixels. We added data boosts like resizing, rescaling, flipping, rotating, zooming, and adjusting contrast. Figure 3.7 displays the images for this study.

	
Augmented Dyskeratotic	**Augmented Metaplastic**

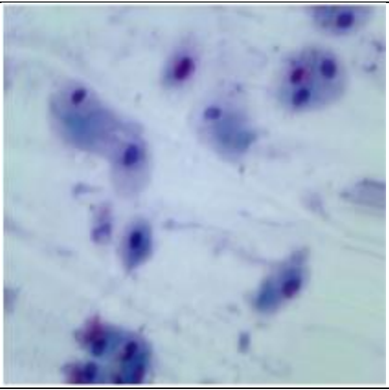
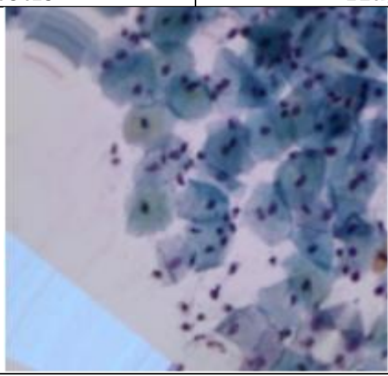
	
Augmented Koilocytotic	**Augmented Parabasal**
	
Augmented Superficial-Intermediate	

Figure 3.7: Samples of the augmented images

3.2.4 Experimental Setup

Table 3.1 Experimental setup of all model

Setup	Values
Activasion functions	Relu, Softmaxs
Optimizers	Adagrad, Adam
Learnig rates	0.001, 0.01 and 0.0001.
Entropy	categoricals cross-entropy
Metrics focused	Acuracy, Precisions, Recal and F1-scores
Epochs	50
Patience	5, and 10
Batch sizes	16, and 32

3.2.5 Models Selecsion

In this step, neural networks are used as classification tools because they can accurately classify each class. We are coming up with three types of approaches to accurately identify images, the first of which is Transfer learning, the second is Deep convolutional neural network and the third is ensemble learning. For transfer learning, we used four tested transfer learning models: EfficientNetB1, MobileNetV3, DenseNet211, and ResNet150. For deep convolusional neurals network, or D-CNNs, we tried Alex Net, LeNet - 5, Highway Net, and ZF Net. Also, We built an ensembles architecture called AZL, there are combines Alex Net, ZF Net, and LeNet - 5. All choices stem from their strong track record in spotting cervical cancer. They reach high accuracy with fewer parameters and less compute. We ran tests by adding extra layers. We tested SELU, but it did not work well. Softmax in the output layer sorted images by disease type. In the end, the AZL ensemble performed best.

3.2.6 Model Training and Evaluation

These models aim for high accuracy through low parameter counts and light compute needs. We optimized the model before training. We balanced classes first. Then we devide the dataset into train, test, and validation. An early stopping callback prevented overfitting. Patience was five, so training halted if validation loss rose for five epochs. Batch size 16 took too long and caused overfitting. So we switched to 32. We tuned batch size with learning rate and optimizer settings. All models used a performance matrix. Adagrad and SGD gave poor results. Adam with a 0.0001 learning rate worked better. On testing set, we measured precition, loss, recal, F1-scores, and overall performance.

3.3 Project Plan

Good planning matters in any project. We planned for one year. But we finished in three months. Smart planning led to success. The timeline appears below.

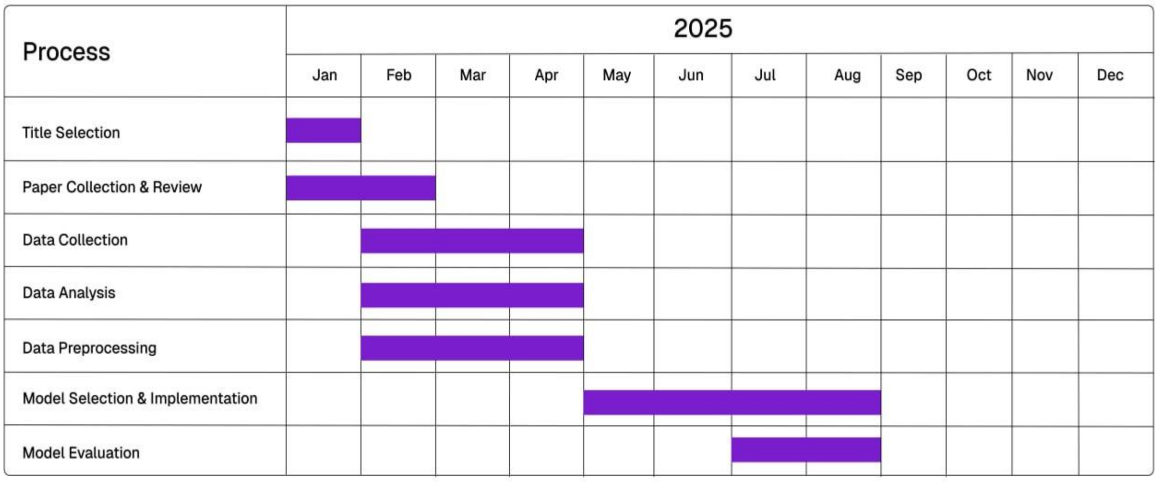


Figure 3.8 Project Timeline

3.4 Task Allocation

The cervical cancer detection project was originally planned for a year but we completed it in just three months. The work involved dataset preparation, processing, implementation of all models and experimental evaluation as well as development of hybrid models. To ensure systematic progress and completion within the planned time frame, the project timeline was divided into 48 weeks with specific tasks assigned to each phase. This structured timeline allows for flexibility in refining the models, performing comparative analyses and preparing documentation.

Tasks	Weeks																		
	12	14	16	18	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48
Data collection																			
Preprocess all the data																			
Model Development																			
Model training																			
Prepare Reports																			
Application																			

Figure 3.9 Task Allocation

3.5 Summary

This study presented an automated cervical cancer classification framework using the deep learning technique. The study began by collecting and preparing a multi-cancer dataset containing approximately 25,000 cervical cancer images that were divided into five classes. These images were preprocessed, which included resizing, rescaling, flipping, rotation, zooming, and contrasting. Also, error level analysis was employed to detect subtle features within the images and highlight anomalies. Three approaches were applied to ensure efficient classification, namely D-CNNs, transfer learning, and ensemble learning. For D-CNNs, we picked AlexNet, ZFNet, LeNet-5, and HighwayNet. For transfer learning, we chose EfficientNetB0, ResNet50, MobileNetV2, and DenseNet201. AZL served as the ensemble. Models training with Adam optimizers, categoricals cros-entropy losses, batch sizes is 16 and 32. Early stopping prevented overfitting. During the experiment, various optimization techniques were combined, although some configurations such as SELU activation and Adagrad algorithm can provide strong results and we achieved better performance with the combination of Adam optimizers and a learing rate was 0.0001 and 0.001. We utilized evaluation metrics including accuracys, precition, recal, and f1-scores to assess the model's performance. Leveraging these parametrs, the integration of various framework has demonstrated an enhancement in the model's performance and diagnostic precition.

Chapter 4

Implementation and Results

Chapter covers how we built the suggested models and tested them. It shows results from tests and reviews how well they worked.

4.1 Environment Setup

Setting up a suitable environment for implementing and testing deep learning models is crucial for a successful project, so this setup includes both hardware and software requirements to ensure seamless development. The study ran tests on Google Colab with the Keras library. We used TensorFlow, a common tool for deep learning, to build machine learning methods. Each model ran fast on cloud servers with a Tesla GPU in Google Colab. That setup offers 6 to 7 GB of Random Access Memory and 300 to 320 GB of GPU power for quick tasks. Cloud platforms like Colab also skip hardware barriers. This lets models train and test without issues. The Keras link to TensorFlow makes deep learning steps easier. It also keeps results steady across various setups.

4.2 Performance Matrix

We applied a performanc matric spot correct and incorrect positive class and negative class. Also pinpoints key spots in the data set. A log scale helps spot those spots fast. Such a matrix sums up model results in a clear grid. It lists counts from the model's choices. True hits mean right guesses; false ones mean wrong guesses. We gauged test outcomes with this models performanc matric.

TP: Models spots just positives classes right.

TN: Models spots just negatives class right.

FP: Models wrongly spots a positives classes.

FN: Models wrongly spots a negatives classes.

Laws of Accuracy: This measures right the model:

$$\text{Accuracy} = \frac{TruePositive+TrueNegative}{TruePositive+TrueNegative+FalsePositive+FalseNegative} \quad (1)$$

Laws of Precition: Precition checks if positive picks are real:

$$\text{Precition} = \frac{TruePosotive}{TruePositive+FalsePositive} \quad (2)$$

Laws of Recal: This shows share of real positives caught:

$$\text{Recal} = \frac{TruePositive}{TruePosotive+FalseNegative} \quad (3)$$

Laws of F-Scores: F1-scores performs significantly better on imbalanced datasets and considers both false negative and false positive:

$$\text{F1} - \text{scores} = \frac{2*(Precition*Recal)}{(Precition+Recal)} \quad (4)$$

The study also used loss curves and confusion matrices to check model performance.

4.3 Observation 1- Efficacy of Transfers Learing

We tested 4 transfers learing setups: EfficientNetB1, MobileNetV3, DenseNet211, and ResNet150. This part reviews their results. EfficientNetB1 topped the list at 99.86% accuracy. MobileNetV3 came last at 94.86% accuracy.

Table 4.1: Accuracy for cervicals cell cancers Classify

Method	**Testing Result**	**Train Result**
EfficientNetB1	99.85%	97.98%
MobilenetV3	94.85%	88.71%
Densenet211	98.61%	94.31%
ResNet150	98.91%	95.98%

Tables 4.2: Precisions, Recal, F1-scores results for transfer learning

EfficientNetB1					
	Dyskerattic	Koilcytotic	Metaplatic	Parabasal	Superficial-Intermeiat
Precisions	99%	99%	99%	99%	99%
Recal	99%	99%	99%	100%	100%
F1-scores	99%	99%	99%	99%	99%
Support	1000	985	1021	989	1005
MobilenetV3					
	Dyskerattic	Koilcytotic	Metaplatic	Parabasal	Superficial-Intermeiat
Precisions	94%	89%	97%	99%	93%
Recal	92%	90%	94%	99%	97%
F1-scores	93%	89%	96%	99%	95%

Support	1000	985	1021	989	1005
Densenet211					
	Dyskerattic	Koilcytotic	Metaplatic	Parabasal	Superficial-Intermeiat
Precisions	98%	97%	99%	100%	99%
Recal	98%	98%	99%	100%	99%
F1-scores	98%	97%	99%	100%	99%
Support	1000	985	1021	989	1005
ResNet150					
	Dyskerattic	Koilcytotic	Metaplatic	Parabasal	Superficial-Intermeiat
Precisions	99%	98%	99%	100%	99%
Recal	98%	97%	99%	100%	100%
F1-scores	99%	98%	99%	100%	99%
Support	1000	985	1021	989	1005

Table 4.2 lists precision scores for each model on the test data. EfficientNetB1, DenseNet211, and ResNet150 stood out among the four. These models spotted and sorted cervical cancer cells with high accuracy. EfficientNetB1 topped them all. MobilenetV3 lagged far behind.

In the confusion matrix, we set zero for Dyskeratotic cells, one for Koilocytotics, two for Metaplastics, three for Parabasals, and four for Superficial-Intermediates. Figure 4.1 displays confusion matrices for the transfer learning setups.

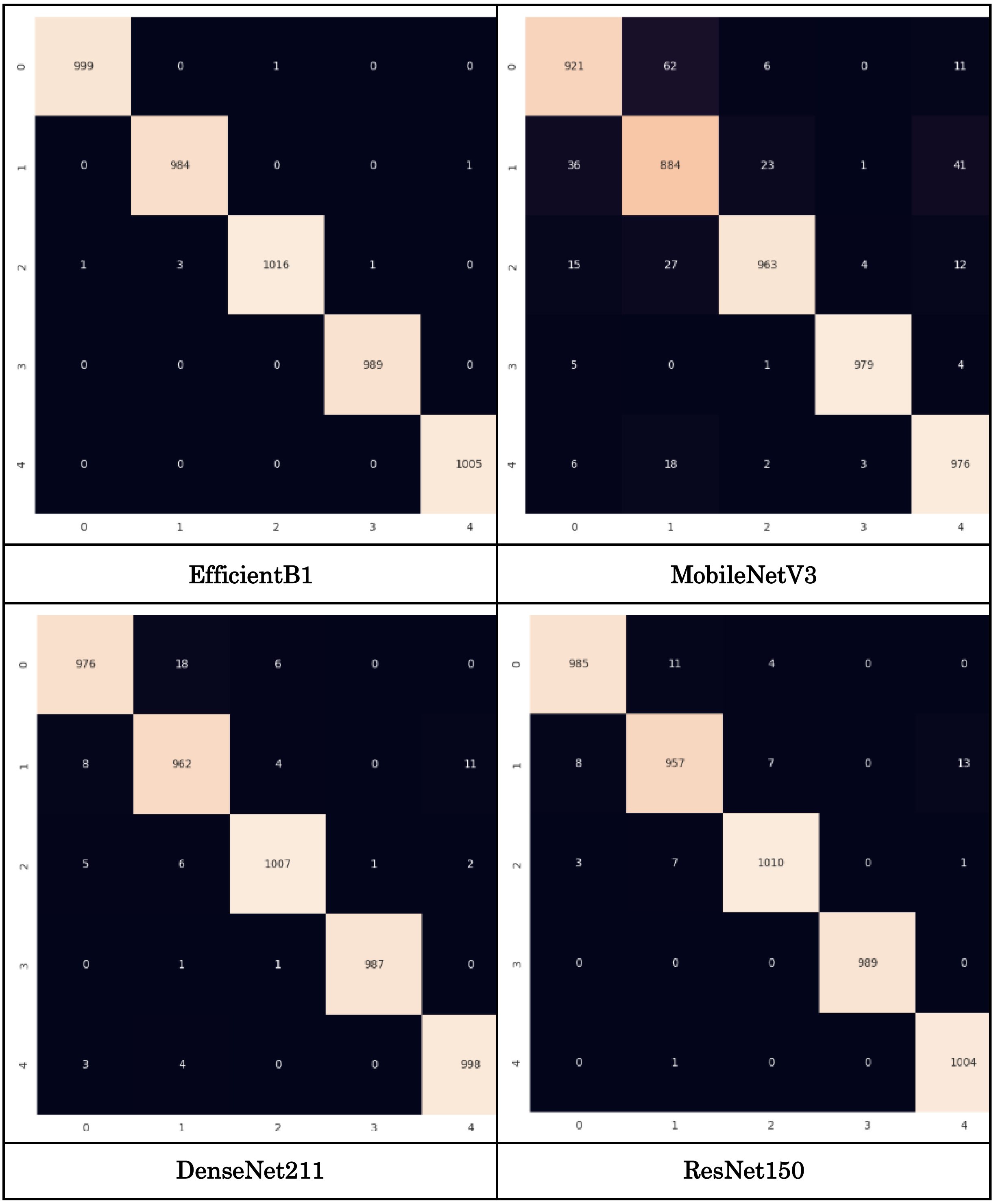
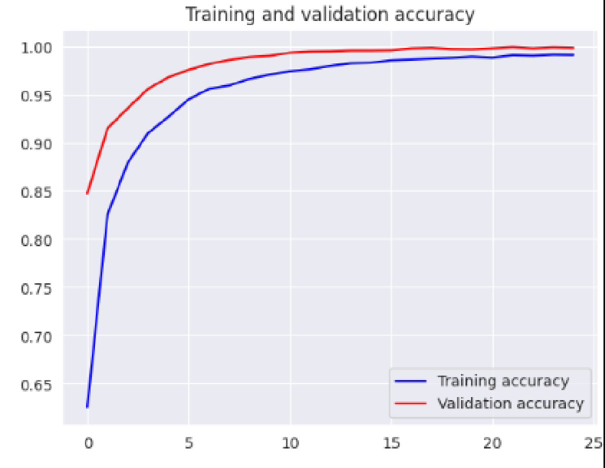
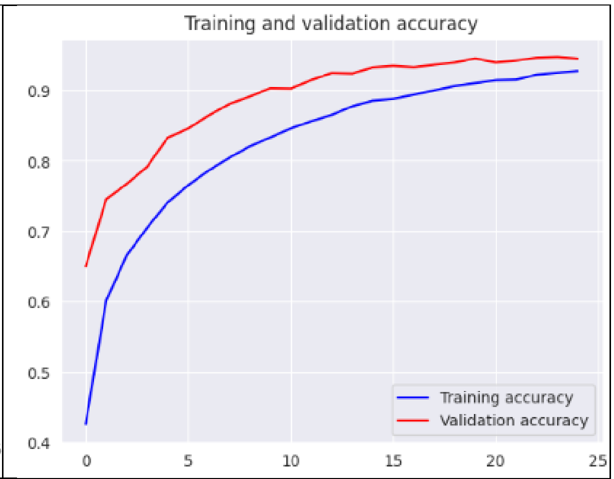


Figure 4.1: Confusion matrices of transfers learning.

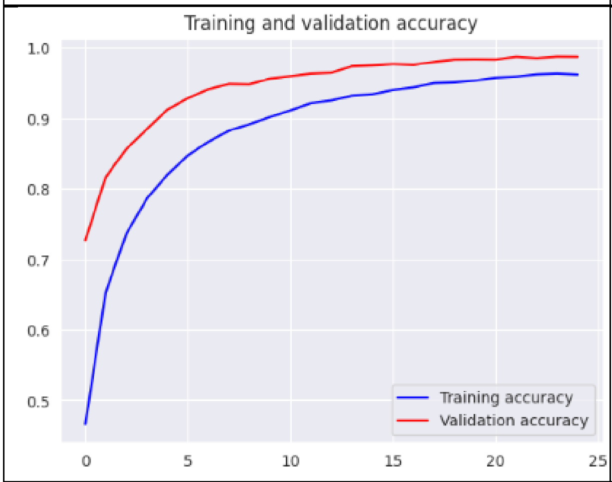
In Figure 4.2, the model's traing and validations relationships are illustrated, with the x-axis denoting the number of epoch and the y-axis indicating the percentage of accuracy and losses. In this graph, the yellow line represents validations accuracy, while the blue line indicates traing accuracy. The graph shows that EfficientNetB1 achieves the highest accuracy in both traing and validation. Conversely, MobilenetV3 exhibits the lowest accuracy in both traing and validations.



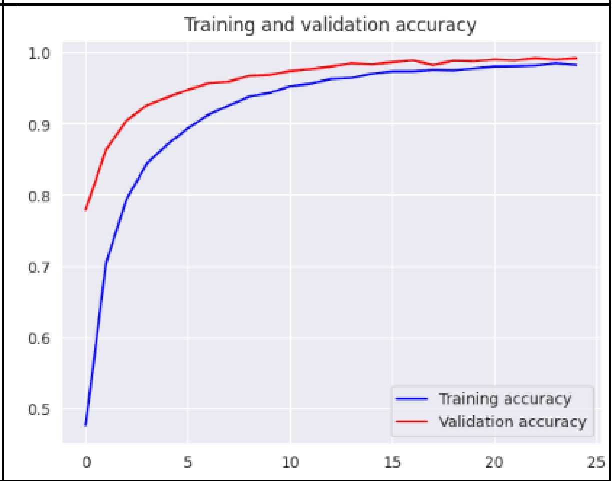
EfficientNetB1



MobilenetV3



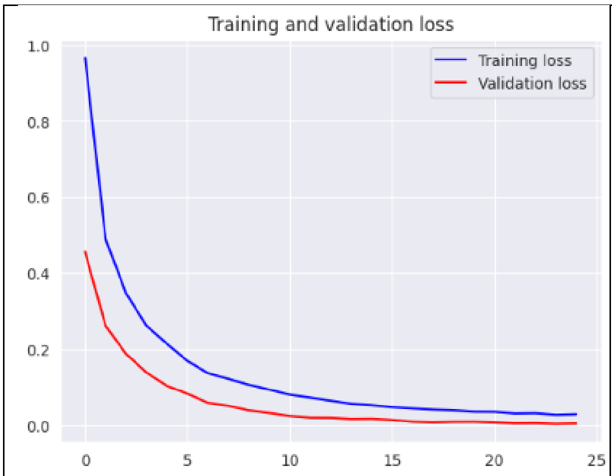
Densenet211



Resnet150

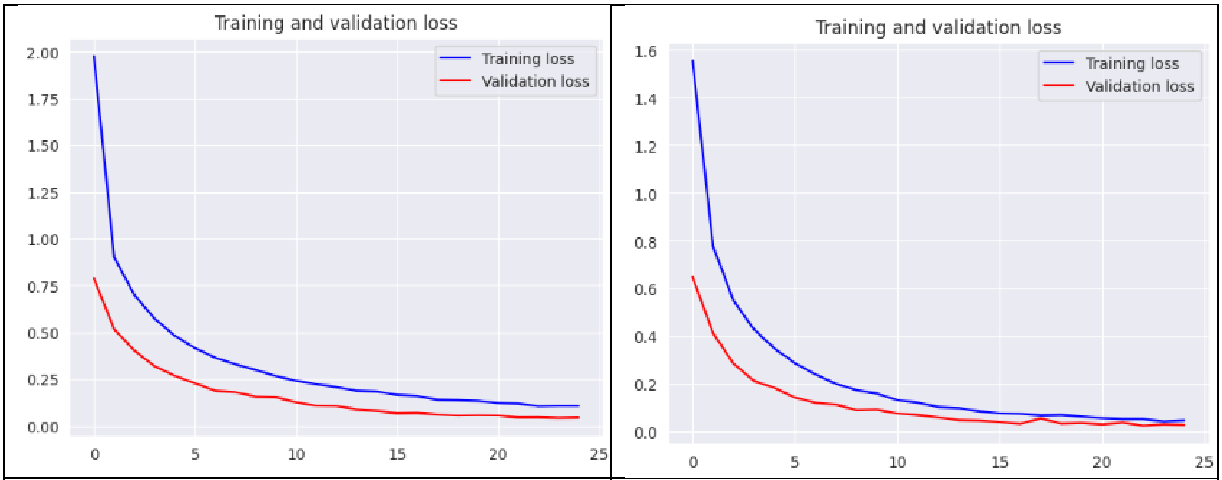
Figures 4.2: Accuracy of Training and Validation

In the shows Figures 4.3 graphs losses over time. The yellow line tracks validation loss; blue shows training loss. EfficientNetB1 claims the lowest losses for both. DenseNet211 follows close. MobilenetV3 suffers the highest losses.



EfficientNetB1

MobilenetV3



Densenet211	Resnet150

Figure 4.3: Losses of Traing and Valdiation

4.4 Observation 2- Evaluating of D-CNN

We tested 4 classic DCNN model likes: Alex Net, Highway Net, ZF Net, and Le Net. This part covers their results.

Table 4.3: Accuracy of the D-CNN models for cervicals cell cancers classfy

Method	Testing Result	Train Result
Alex Net	99.75%	96.07%
Highway Net	99.81%	97.33%
Zf Net	99.37%	97.06%
LeNet - 5	87.85%	86.95%

HighwayNet led with 99.80% accuracy. LeNet-5 trailed at 87.84%. HighwayNet proved sharpest to cervicals cell cancers classification. Transfers learing boosted accuracy beyond these baselines.

Table 4.4 details precision for each on test data. Alex Net, ZF Net, and Highway Net excelled. All 3 nailed cancer cell detection and sorting. Alex Net shone brightest. LeNet - 5 fell shortest.

Table 4.4: PreciTion, recal, f1-scores of D-CNNs mdoels

Alex Net					
	Dyskerattic	Koilcytotic	Metaplatic	Parabasal	Superficil-Intermeiat
Precisions	100%	99%	100%	100%	100%
Recal	100%	100%	100%	100%	100%
F1-scores	100%	100%	100%	100%	100%

Support	1000	985	1022	988	1006
LeNet - 5					
	Dyskerattic	Koilcytotic	Metaplatic	Parabasals	Superficil-Intermeiats
Precisions	86.01%	82.01%	85.05%	96.07%	91.03%
Recal	86.02%	79.05%	92.01%	97.06%	86.07%
F1scores	86.03%	80.05%	88.01%	96.09%	88.06%
Supports	1000	985	1022	988	1006
Highway Net					
	Dyskerattic	Koilcytotic	Metaplatic	Parabasals	Superficil-Intermeiat
Precisions	99.03%	99.95%	99.99%	99.93%	99.94%
Recal	99.96%	99.05%	99.95%	99.99%	99.92%
F1scores	99.97%	99.95%	99.93%	99.92%	99.94%
Supports	1000	986	1022	988	1006
Zf Net					
	Dyskerattic	Koilcytotic	Metaplatic	Parabasals	Superficil-Intermeiat
Precisions	99%	99%	100%	100%	100%
Recal	100%	99%	98%	100%	100%
F1-scores	99%	99%	99%	100%	100%
Support	1000	985	1021	989	1005

In the confusion matrix, we have assigned zero to Dyskeratotics, one to Koilocytotics, two to Metaplastics, three to Parabasals, and four to Superficil-Intermediates. Figure 4.4 displays the four confusion matrics for the D-CNNs.

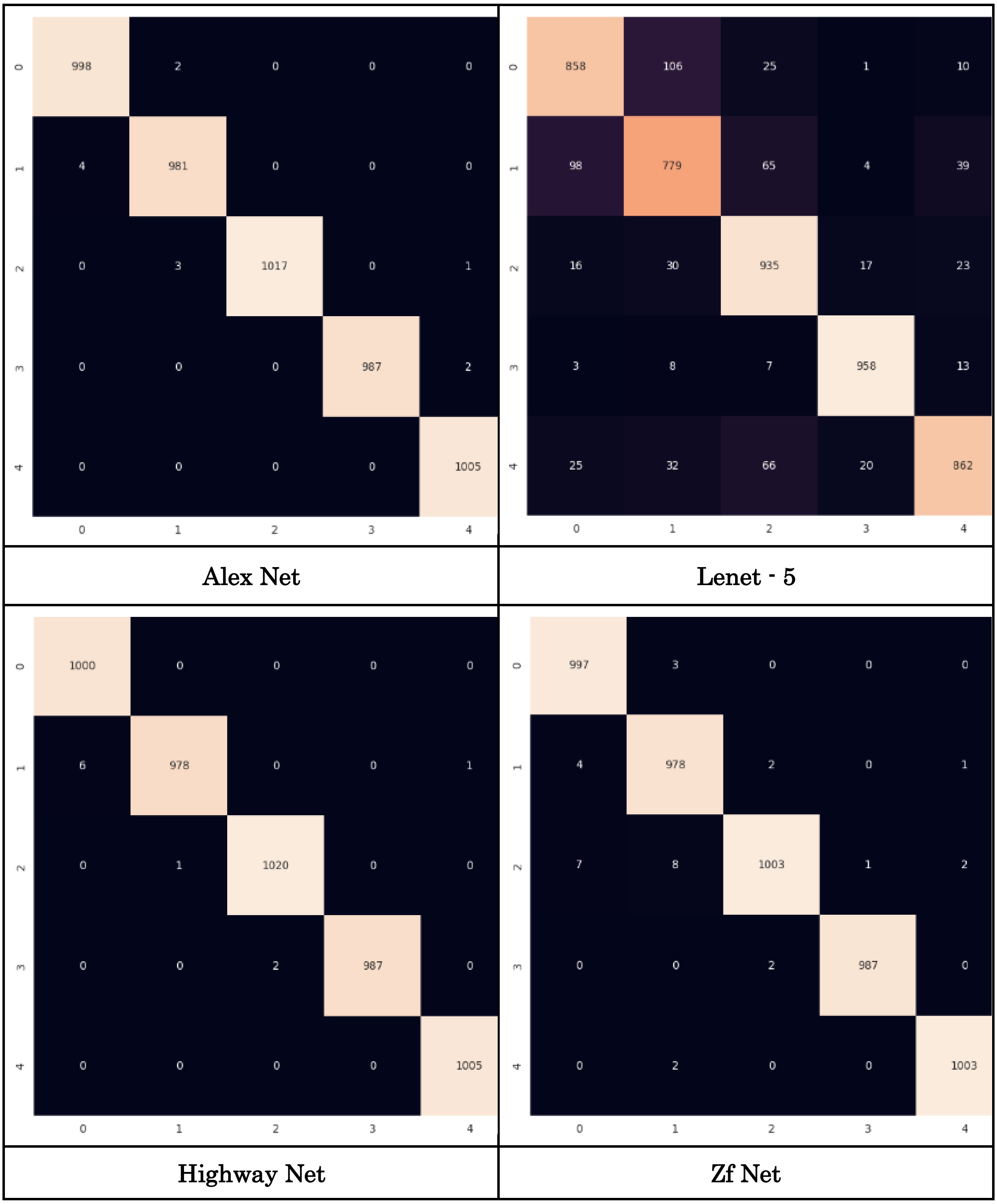
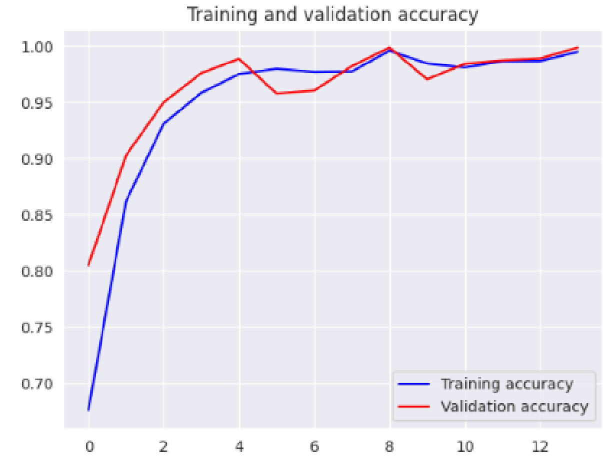
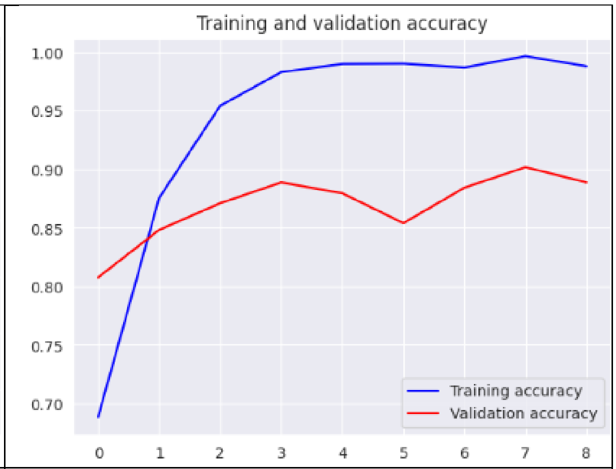


Figure 4.4: Confusion matrices of the D-CNNs for cervical cancer classifcation

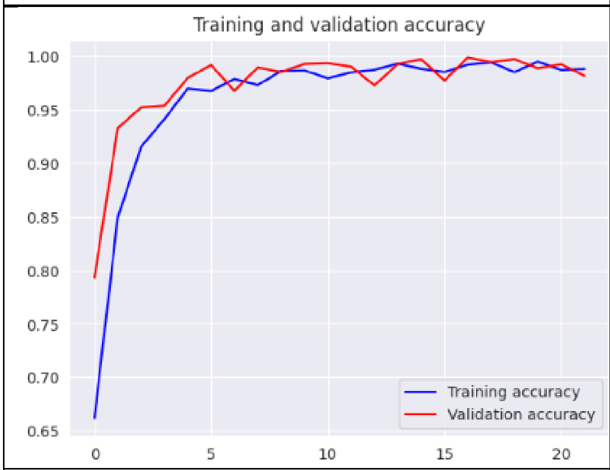
Figure 4.5 charts accuracy trends. X-axis marks epochs; Y-axis shows accuracy and loss. Yellow traces validation accuracy; blue tracks training. AlexNet peaks highest in both. LeNet-5 dips lowest. Compared to transfer learning, these CNNs deliver stronger outcomes.



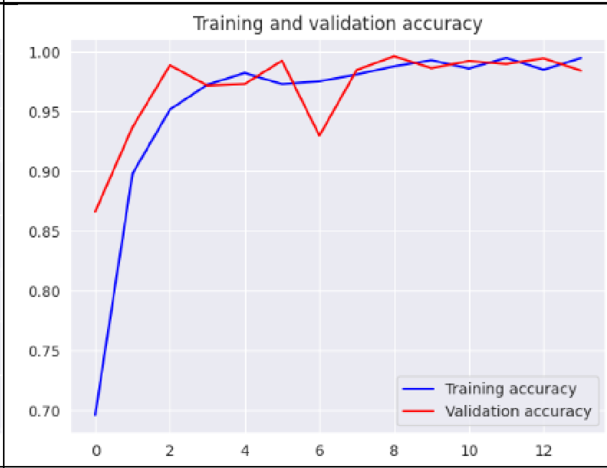
Alex Net



LeNet - 5



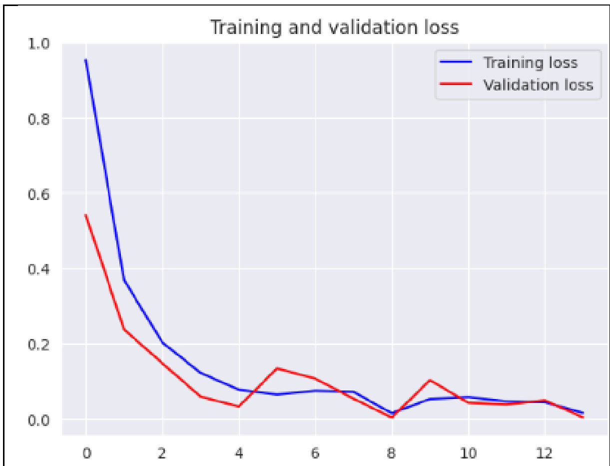
HighWay Net



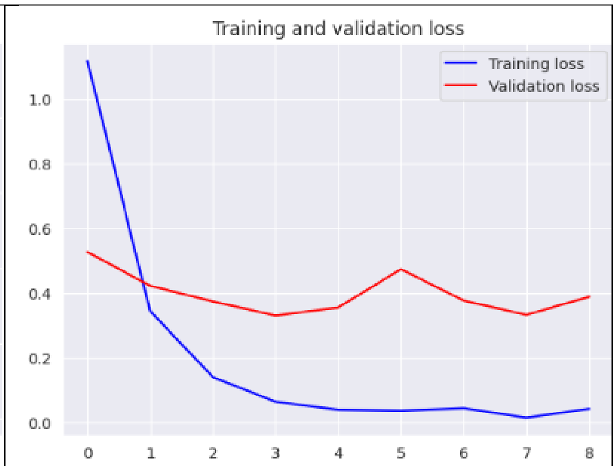
Zf Net

Figures 4.5: Accuracy of Traing and validation

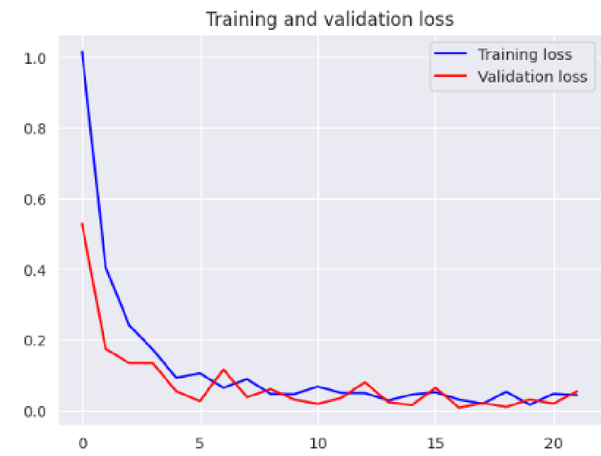
Figures 4.6 plots losses. Yellow marks validation; blue shows training. AlexNet holds the lowest in both. ZFNet ranks second lowest. LeNet-5 bears the highest.



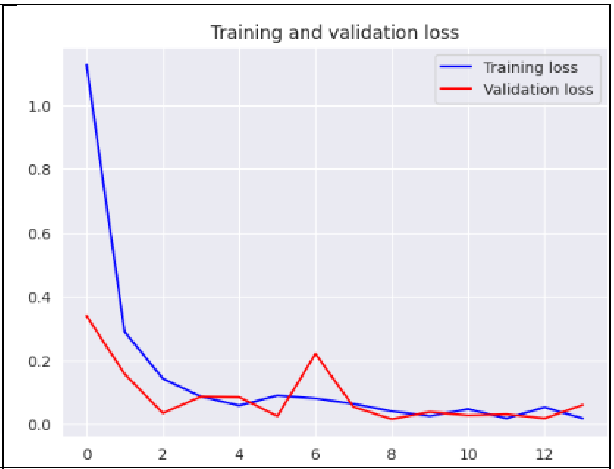
Alex Net



LeNet - 5



HighWay Net



Zf Net

Figures 4.6: Losses of Traing and Valdiation

4.5 Observation 3- Evaluation of Ensembles Models

This work now shifts to the AZL ensemble, blending AlexNet, ZFNet, and LeNet. It merges their strengths in feature spotting and classification to sharpen diagnosis. We explain AZL's build, testing, and side-by-side review with prior models. The next part outlines its structure and steps.

4.5.1. Model Development

Our study aimed to build ensembled models for simple classification of cervical cancer. We developed this ensemble model to spot and sort cervical cancer with ease. The key benefit of hybrid models is abiliti to fixes error from a single model's wrong guesses. In this work, we picked AlexNet, ZFNet, and LeNet for the ensemble. We called its AZLs. That models reached 99.93% accuracys in the classification's tasks. We built AZL model to pair strong and weak classifiers. The ensemble adds up probability scores from the 3 CNN framework like Alex Net, ZF Net, and Le Net to get the total probabilities of each classes.

Figure 4.7 lays out the structures of these three CNN frameworks: Alex Net, ZF Net, and Le Net. Alex Net includes Conv2D layers, MaxPooling2D, dense layers, and dropout. It details the filter setup, leading to the final classification. LeNet, compared here with AlexNet and ZFNet, features convolutional layers, averages poling, denses layers, and dropouts, all flowing to this output classifications. The ensembles hybrid models begins compilations also finishes as a complete-to-train also evaluate setup. It turns into a practical tool.

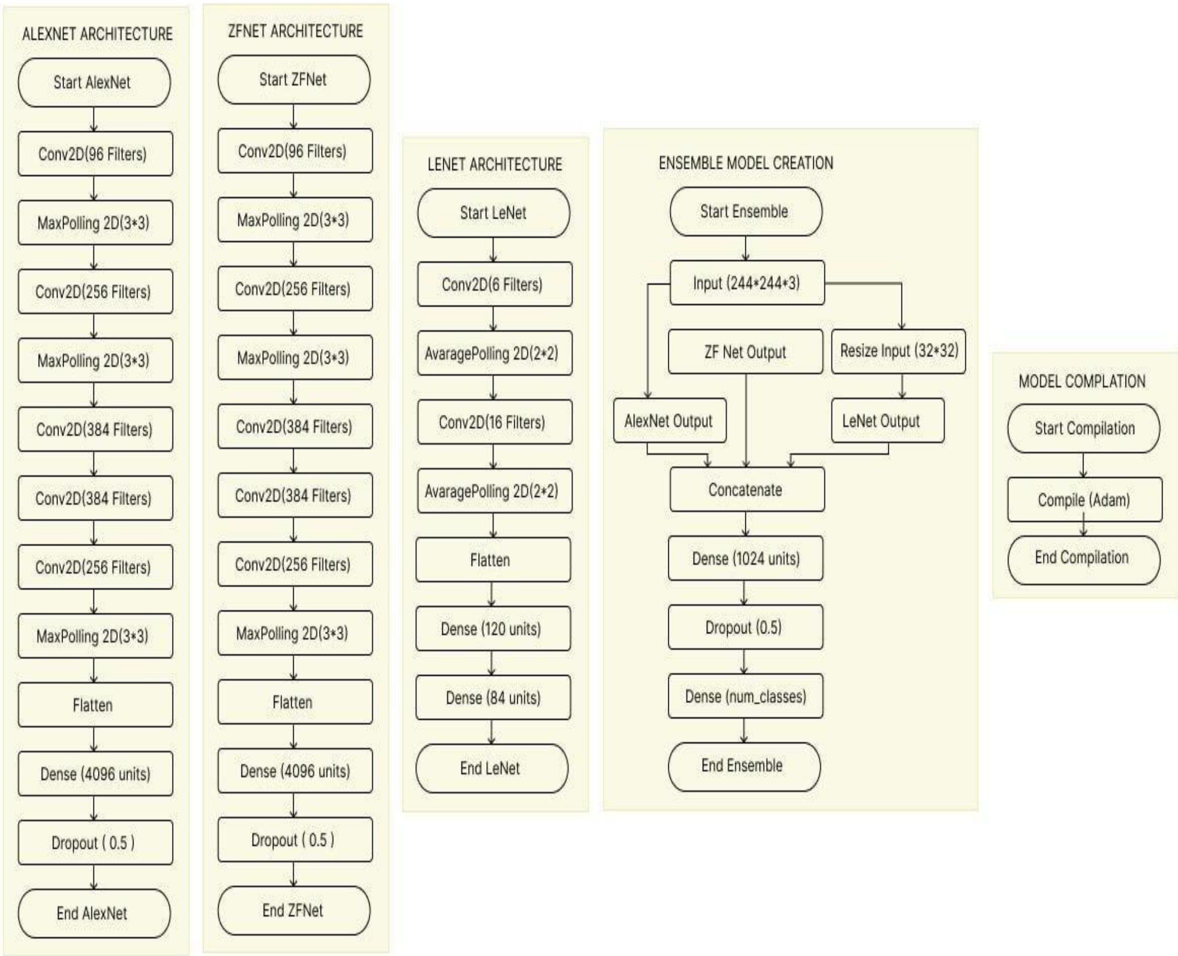


Figure 4.7: Proposed AZL ensemble model flowchart.

4.5.2. Algorithm Ensemble procedure

Algorithm 1 outlines the steps to create the ensemble model.

i. **Inputs**: [Alex Net, Zf Net, LeNet - 5], tests_datasets

ii. **Outputs**: ensembles_nets

iii. **allmodel** ← [Alex Net, ZF Net, Le Net]

iv. **for** every models do

i. ensembles_nets.compiles (optimizers='Adam', losses='categoricals_cross_entropy', metrices=['accurcy'])

i. **finish**

ii. **pred_arrays** ← array (prediction)

i. **pred_sums** ← sum (pred_arrays, axis=0)

i. **ensemble_preds** ← argmax (pred_sums, axis=1)

i. **ensembles_nets** ← ensembles_preds

outputs ensembles_nets

Tables 4.5 details the ensemble model formed by blending AlexNet, ZFNet, and LeNet. It separates five class there are: Dyskeratotics, Koilocytotics, Metaplastics, Parabasals, Superficil-Intermediates. Fors every classes, the table lists precition, recal, F1-scores, and support values. Only ensemble scored 100% in precition, recal, and F1-scores acrosses all class. This points to perfect classification results.

Table 4.5. Precition, Recal, F1-scores of ensembles techniques

Hybrid Models (Alex Net, Zf Net, LeNet - 5)					
	Dyskerattic	Koilcytotic	Metaplatic	Parabasal	Superficial-Intermeiat
Precisions	99.99%	99.99%	99.99%	99.99%	99.99%
Recal	99.99%	99.99%	99.99%	99.99%	99.99%
F1-scores	99.99%	99.99%	99.99%	99.99%	99.99%
Support	1000	985	1021	989	1005

4.5.3. Ensemble model's confusion matrix

The results for these 5 class are represented by the confusion matric. We assigned zero for Dyskeratotics, one for Koilocytotics, two for Metaplastics, three for Parabasals, and four for Superficil-Intermediates. It monitors accurate and inaccurate classifications for each class. The initial row displays 1001 of 1001 Dyskeratotics samples correctly predicted. The 2nd row contains 982 correct samples of 986 Koilocytotics. The 3rd row corresponds to 1022 of 1022 Metaplastics samples. The 4th row correctly identifies 988 of 988 Parabasals samples. The 5th row secures 1006 of 1006 Superficil-Intermediates samples. These impressive figures account for the model's leading performance. Figures 4.8 shows the confution matric for the ensembles.

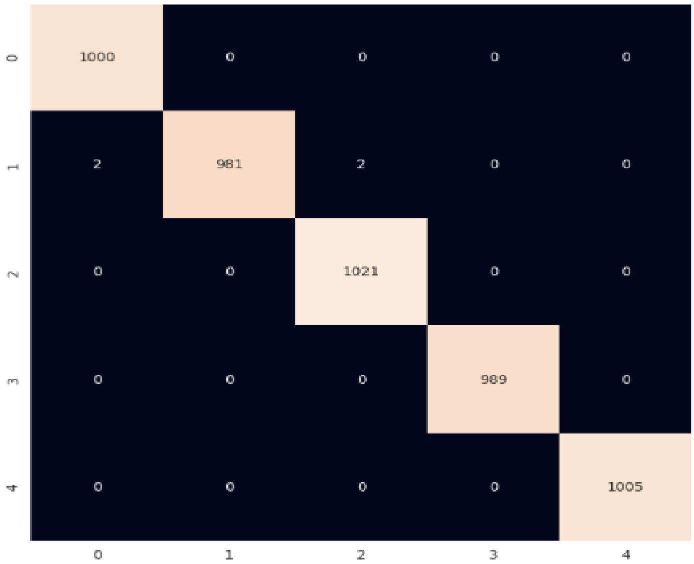
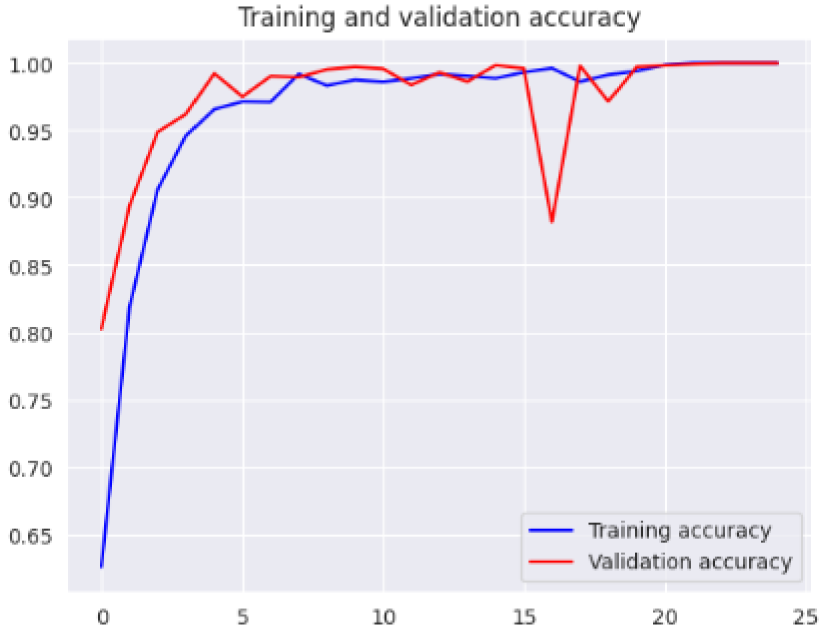
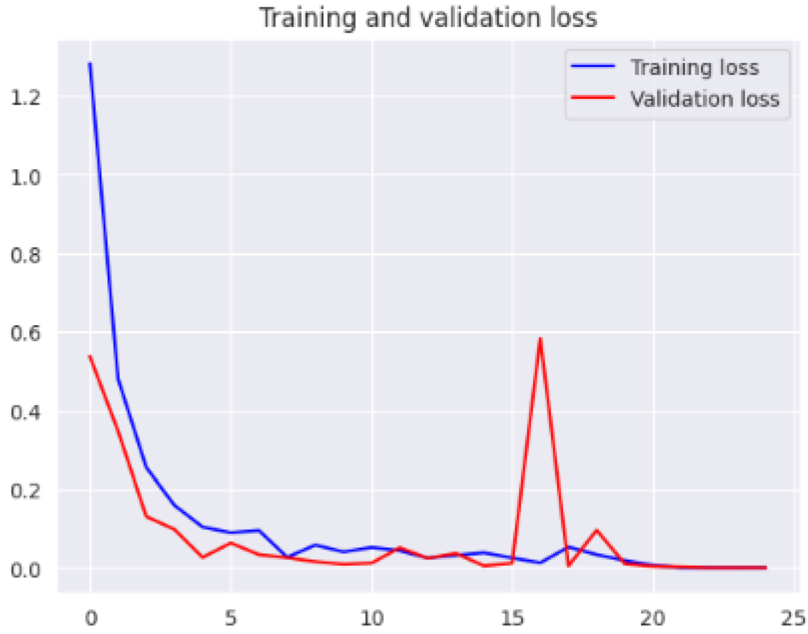


Figure 4.8: Confusion matrix of the Ensemble model.

Figure 4.9 and Figure 4.10 show the training and validation accuracy and loss curve of the graph plots model performance. The x-axis marks epochs; the y-axis shows accuracy and loss in percent. A yellow line tracks validation accuracy. A blue line follows training accuracy. The ensemble fits data well. As loss drops, validation accuracy rises over time. The loss curve confirms solid outcomes.



Figures 4.9: Accuracy of Training and validation



Figures 4.10: Loses of Training and validation

4.6 Results and Discussion

This research applies deep learning with three setups. Each handles detection and precise classification of cervical cancer images. The deep learning approaches delivered strong results.

Table 4.6: Compares accuracy from transfer learning, D-CNNs, and ensemble models.

Method	Models	Result
Transfers Learnings model	EfficientNetB1	99.86%
	MobileNetV3	94.86%
	DenseNet211	98.60%
	Resnet150	98.90%
D-CNNs	Alex Net	99.76%
	LeNet - 5	87.84%
	HighWay Net	99.80%
	Zf Net	99.36%
Ensembles Learnings	AZL (Alex Net, Zf net, LeNet - 5)	99.92%

In the 1st observation compared 4 transfers learing setups EfficientNetB1, MobileNetV3, DenseNet211, and ResNet150 on 25,000 images of cervical cancer across five types. Transfer learning draws on skills from models pre-trained on ImageNet to spot cancer signs [12]. This cuts down on data needs and quickens training, easing cancer detection [46]. Big datasets helped test how well the models spot textures and patterns. Data tweaks boosted their scores. Fine-tuning and learning rates lifted model performance a lot, as noted in [47].

In the 2nd test, 4 DCNNs designs Alex Net, LeNet - 5, Highway Net, and ZF Net tackled cancer detection and sorting. Alex Net stood out with top results. These setups handle images well, no matter the depth or detail. Deep layers and ReLU functions in Alex Net shine for big image sets [48]. Highway Net aids deep training by letting data skip layers. It also reduces any potential invisible gradient issues, if they are present [49]. The authors [19] acknowledge that Zf Net represents an enhanced variant of Alex Net, with adjustments made to the convolusional filters and hyperparameters, leading to superior performances. Alex Net leverages its strengths to generate visual patterns specifically adapted to cervicals cell cancers image [12]. We concur with [46] Thus, the Alex Net models is capable of efficiently identifying precancerus lesio or cancerous alteration.

In the 3rd test built an ensembles models called AZL for cancers classification and sorting. Base models with varied views of the data cut errors through smart mixing [48]. Ensemble methods work well for this task, but key factors matter.

Transfer learning scores were strong. EfficientNetB1 hit 99.87% accuracy. ResNet150 reached 98.91%. DenseNet211 scored 98.61%. MobileNetV3 lagged at 94.87%. For deep CNNs, Highway Net led with 99.81%. Alex Net followed at 99.77%. ZF Net got 99.37%. LeNet-5 scored lowest at 87.85%. The AZL ensemble, blending Alex Net, ZF Net, and LeNet-5, hit 99.93%. EfficientNetB1 and Highway Net topped their groups. Highway Net edged out Alex Net. LeNet - 5 and MobileNetV3 trailed in their lines. The ensemble led overall and nailed cancer detection.

4.7 Summary

This work applies deep learning in three tests to spot and sort cancer images with care. Models delivered solid outcomes. The review compares them all. EfficientNetB1 topped transfer learning at 99.87%, while MobileNetV3 bottomed at 94.87%. Highway Net led deep CNNs at 99.81%, with LeNet - 5 at 87.85%. AZL reached 99.93%. Top picks shone in their fields. The ensemble gave the best accuracy for cancer tasks.

Chapter 5
Engineering Standards and Design Challenges

Chapter covers key engineering rules, standards, and issue from this thesis. It makes sure the design fits technical, ethical, and social needs.

5.1 Compliance with the Standards

5.1.1 Software Standards

Required softwares for this project:

- Google Chrome or Microsoft Edge
- Python 3.9
- Tensor flow
- Matplotlib
- cv2
- Jupiter or Google Colab or Kaggle

5.1.2 Hardware Standards

The required software for this project:

- Windows 11 operating system
- Hard Disk 512 GB
- 8 GB RAM

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impacts on Life

The tool to spot cervical cancer can change lives, mainly in health care. This cancer kills many women around the world. But early checks can stop it or treat it well. Deep learning helps build an auto system for quick, right calls by doctors. It cuts down on hand checks and mistakes. Early finds lead to better care and longer life. The project tackles spots with few doctors or tools. These systems let health workers scan fast. Women in poor areas get checks and help sooner. This lowers deaths and boosts life quality.

5.2.2 Impact on Society & Environment

The new tool for cervical cancer detection aids society a lot. It finds this top cancer killer in women fast and right. Deep learning auto-checks cut slow, wrong hand scans. Pathologists get solid facts for choices. Quick finds raise cure odds. Better care follows, with higher survival. This tech helps poor lands short on experts and gear.

From a societal perspective, this framework provides healthcare providers with a cost-effective and scalable diagnostic solution. This in turn reduces diagnostic errors and helps build patient confidence in automated healthcare systems. This method eases the load on health staff. They can spend time on patients, not repeat checks. As a result, it contributes to better healthcare outcomes and increases overall public awareness about cervical cancer.

This project is highly sustainable in terms of environmental impact as it relies primarily on computational resources rather than physical medical supplies or invasive testing procedures. Image-based diagnosis reduces the reliance on disposable laboratories and physical biopsies, thereby reducing medical waste. Also, since this February can be integrated into a telemedicine platform, it reduces the need for frequent hospital visits and long-distance travel, thereby reducing the overall carbon footprint.

5.2.3 Ethical Aspects

Ethics matter in medical work, above all with private data like cancer images. This project strictly adheres to ethical standards to ensure transparency, confidentiality and responsible use of data. Although a publicly available dataset was used, the risks associated with breaching confidentiality were also minimized, although no direct contact with patients or personal information was involved in completing this project.

However, careful attention was paid to maintaining confidentiality and ensuring that the dataset was used for academic and research purposes only. Another key ethical aspect is the integrity of the research process, especially when all data set preprocessing, model training and evaluation steps were conducted in a transparent manner to avoid data manipulation. All external references were used appropriately to maintain academic integrity.

Since the system is designed to support medical diagnosis, ethical responsibility is the ability to prevent over-reliance on the model without human supervision. The developed framework was intended to assist pathologists, recognizing the risks of misclassification and emphasizing the importance of expert validation in clinical applications. In the end, this work weighs social and ethical sides. It seeks to aid fast, true cancer checks and better health reach.

5.2.4 Sustainability Plan

The development of a cervical cancer detection system is essential to diverse this the solution simualtion to divide the values beyond of the initial development phase. Since it is based on continuous learning, it is designed with measurement accuracy and long-term usability in mind. The system is capable of being updated with new data sets as more cervical cancer images become available, allowing for continued improvements in accuracy and longevity. By incorporating these techniques, the model can adapt to evolving diagnostic needs and remain relevant in medical applications.

The system uses open-source libraries like TensorFlow, karas, and OpenCV, which are widely supported by the research and development communities, to ensure the stability of the logic. This reduces the dependency on expensive proprietary tools and ensures future compatibility.

From a healthcare perspective, the project supports social and medical sustainability by reducing the diagnostic burden on pathologists and enabling early detection of cervical cancer in limited settings. The automated system can serve as a decision support tool that ensures timely intervention and reduces mortality.

Financial and operational sustainability is maintained through potential partnerships with healthcare organizations and government initiatives focused on cancer prevention. The system is positioned as a cost-effective solution that increases diagnostic accuracy. It can be deployed in hospitals and on telemedicine platforms. Ongoing updates, steady checks, and input from health experts will keep the system precise, dependable, and strong in battling cervical cancer.

5.3 Project Management and Financial Analysis

- Project Timeline:
    - A. Phase 1: Project Planning and Research (1 week)Phase 2: Reference Paper Collection (1-2 weeks)
    - B. Phase 3: Paper Review (1-2 weeks)
    - C. Phase 4: Data Collection (1-2 weeks)
    - D. Phase 5: Data Analysis (1-2 weeks)
    - E. Phase 6: Data Preprocessing (1-2 weeks)
    - F. Phase 7: Model Implement (1-2 weeks)
    - G. Phase 8: Model Evaluation (1-2 weeks)
    - H. Phase 9: Prototype Design (1 weeks)
    - I. Phase 10: Front End Development (1-2 weeks)
    - J. Phase 11: Deployment & Testing (1-2 week)
- Resources Planing:

A. Equipments and Tool:

- Develop and Test
- Collaboration Tools
- Testing Tools
- Version Control System

B. Softwares and Technology:

- Website Front End Knowledge: Html, Css, Java Script, or React
- Website Back End Knowledge: Node.js, Django, or Flask
- Server Hosting: AWS, Azure, Google Cloud or Hostinger
- Security Software and SSL Certificates

The cost table appears below:

Table 5.1: Cost Estimated Table

SN	Components	Estimated Cost (BDT)

1	Tools and Equipment	4500-6000
2	Software	5000-7000
3	Gathering and handling data	2500-3000
4	Writing reports and documenting information	1500-2000
5	Contingenccy (11% of overall)	1000- 1500
Overall Projected Expense		13500-19000

5.4 Complex Engineering Problem

This thesis tackles a tough engineering task. It blends deep learing and Clinicnal image in a ensembles method of cervicals cell cancers classification. The title is "A Hybrid Approach for Cervical Cancer Classification: Combining D-CNN, Transfer Learning, and Ensemble Models." The work demands strong analysis skills. It handles complex, often incomplete data. It creates new ways to compute results.

5.4.1 Complex Problem Solving

Table 5.2: Mapping with complex problem solving.

EP1 Depth of Knowledge	EP2 Ranges Of Conflictings Requirements	EP3 Depths of Analysiss	EP4 Familiarity of Issue	EP5 Extents of Applicable Codes	EP6 Extents Of Stake-holders Involvement	EP7 Interdependence
✓	✓	✓		✓	✓	

Mapping with KP for EP1

Table 5.3: Mapping with knowledge Profile.

K1 Natural Science	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K3 Comprehension	K8 Research Literature
✓		✓	✓	✓	✓	✓	✓

5.4.1.1 Justification for EP Attributes Mapping

- **EP1 - Depth of Knowledge Required:**

  The EP1 project integrates advanced deep learning models with learning techniques that require strong knowledge of medical imaging data pre-processing and neural network architecture.

- **EP2 - Range of Conflicting Requirements:**

  EP2 Balancing accuracy and computational efficiency also requires a solution, with data set imbalance and overfitting issues creating conflicting requirements.

- **EP3 - Depth ofAnalysis:**

  EP3 was analyzed in depth, including pre-processing and comparative performance of eight individual models and development of hybrid ensemble models.

- **EP5 - Extent of Applicable Codes:**

  EP5 is a python, TensorFlow, karas model implementation with strict standards for international standards in medical research.

- **EP6 - Extent of Stake-holder Involvement:**

  EP6 is a system aimed at supporting pathologists, oncologists and healthcare professionals, and has also shaped the objectives of their demand model.

5.4.1.2 Justification for Knowledge Profile Mapping:

- **K1 - Natural Science:**

  K1 is a natural science that studies the principles of applied biology and medical science, such as cervical cell image analysis.

- **K3 - Engineering Fundamentals:**

  K3 is an engineering fundamentals course that covers the fundamentals of applied computer science and AI, especially neural networks, convolutional backpropagation.

- **K4 - Specialist Knowledge:**

  K4 is Specialist Knowledge which is a deep learning technique applied for medical image classification.

- **K5 - EngineeringDesign:**

  K5 is an end-to-end diagnostic system designed with model development framework and ensemble integration.

- **K6 - EngineeringPractice:**

  K6 Engineering Practice which implements practical solutions using python, TensorFlow, karas, OpenCV, dataset handling and evaluation pipeline.

- **K7 - Comprehension:**

  K7 is a model performance issue, especially overfitting optimizer effects, batch size tuning, and corrective measures have been implemented.

- **K8 - Research Literature:**

- K8 is a literature review on cervical cancer detection that compares with subsequent work and adopts the best performing models.

5.4.2 Engineering Activity

Table 5.4: Mapping with complex engineering activities.

EA1 Ranges of Re source	EA2 Levels of Interactions	EA3 Innovations	EA4 Consequence for society and environments	EA5 Familiaritys
✓	✓	✓	✓	✓

5.4.2.1 Justification for Engineering Activities Mapping:

- **EA1- Range of Resources:**

  EA1 is a project that uses a variety of resources, especially medical imaging datasets, computational resources, and domain knowledge from computer vision.
- **EA2 - Level of Interaction:**

  EA2 is essential for multidisciplinary interactions such as deep learning in computer science, cervical cancer diagnosis in healthcare, and preprocessing and augmentation in data science.
- **EA3 - Innovation:**
- EA3 offers a fresh idea. It builds a hybrid ensemble model. This model reaches top accuracy. It beats single DCNN and transfers learing framework.
- **EA4 - Consequence society environment:**

  EA4 is a program that supports early detection of cervical cancer, reduces mortality, and provides direct social benefits by providing affordable solutions for limited healthcare environments.
- **EA5 - Familiarity:**

  EA5 uses deep learning in a new field. That field is medical image classification, full of challenges.

5.5 Summary

The full project meets key engineering rules. It solves hard problems in building a cervical cancer classification system with deep learning. The team used various software and hardware to run the project. The work has a big social effect. It allows early and right diagnosis of cervical cancer. This cancer kills many women. The method cuts down on manual checks and errors. It boosts survival odds, above all in poor areas. From an environmental perspective, this framework enables a telemedicine-based scanning that reduces invasive testing and medical bills. The sustainability plan ensures long-term usability through continuous updates with new datasets and possible integration into healthcare and telemedicine platforms. The management of this project involved methodological phases including dataset preparation, pre-processing, model implementation evaluation and prototype design as well as deployment. A reason for the advanced knowledge for solving complex problems was demonstrated by solving large-scale optimization problems and complying with international standards and involving healthcare in AI or medicine interdependent domains. The knowledge profile highlights the integration of expert knowledge design practices and literature in the fundamentals of natural sciences, mathematics, engineering. In addition, the high-level engineering activities emphasize resource integration, innovation of ensemble modeling, social benefits and application in a novel domain.

Chapter 6

Conclusion

This chapter outlines the main results and successes of the project. It reviews the research results and total impact.

6.1 Summary

Cervical cancer causes the most deaths in women around the world. We tested one proposed design against another through experiments. These tests used image sets. Our work helps fix limits in later study. We 1st tried the images dataset on Googles Colab. Its ran too slowly. So we switched to the free Kaggle platform for this study. Kaggle gives a free server. It lets us tune settings, train simple models, use ImageNet as a base, and apply different optimizers with ease. Here, we skipped raw patient data. We used second-hand data instead. The Error Level Analysis (ELA) method helped spot any gaps in the images. We resized images to 224x224x3 format. We applied boosts like resizing, rescaling, flipping, rotation, zooming, and contrast changes. These boosts raised model accuracy a lot. Future work should build strong models with mixed data sets and better settings.

We applied deep learning methods, mainly transfers learing, deep convolutionals neurals networks, and group model to spotting, sorting cases. Tests viewed strong gains of finding cervicals cell cancers. Pretrained transfer model, and train on the big datasets like image net, did best. EfficientNetB1 topped accuracy. The DCNNs design, especially HighWay Net, also hit the best score. A group model with Alex Net, ZF Net, and Le Net spotted also sorted cervicals cell cancers well. This tools make detection and sorting straightforward. Deep learning aids pathologists in auto-finding cervical cancer. Our models could change diagnosis in health care. The model trained on one set that misses real-world variety in cases. It may falter on new data with different image types. Boosts helped, but uneven class counts still harm spread to rare cases. The group model adds heavy computing needs. It may not fit low-power or quick-use spots. Still, this tech could cut deaths from cervical cancer.

6.2 Limitation

The limitations of this study, the proposed system relies on a multi-cancer data set that maybe its not fullfill represent to the variability of globally clinical practice cervicals cell cancers case, as changes in image quality and equipment across hospitals or regions may affect the generalizability of the model. Deep learning models require high-performance hardware to train, making large-scale deployment in limited healthcare settings challenging, especially where advanced computational infrastructure is not available. In addition, despite the application of augmentation and early stopping, deep learning models trained on fixed data sets may still be overfitted, which may degrade performance when testing on unseen data from different sources or with rare metastatic cancer variants. For diagnosis, this system only considers histopathological images, which are not combined with other important clinical parameters such as patient genetic markers and laboratory tests, which may increase diagnostic accuracy in real-world situations.

6.3 Future Work

We can boost detection accuracy by testing newer deep learning types like vision transformers or Swin transformers. Later studies might explore mixed-model ways that blend scans with patient health info. This mix could clarify the disease and sharpen diagnosis. XAI tools could make models clearer and stronger. Such steps build trust with doctors.

Moving these models to real use marks a key gain for real change. Adding them to easy apps, like phone-based check tools, aids quick spotting of early cervical cancer. Better computing and image review aim to help patients via fast, right diagnosis. This matters most in poor and middle-income areas hit hard by cervical cancer.

References

[1] D. Singh et al., "Worldwide Estimates of Cervical Cancer Incidence and Mortality in 2020: a Foundational Analysis of the WHO Global Cervical Cancer Elimination Initiative," The Lancet Global Health, vol. 11, no. 2, Dec. 2022, Accessible: https://www.thelancet.com/journals/langlo/article/PIIS2214-109X(22)005010/fulltext

[2] F. Wei, D. Georges, I. Man, I. Baussano, and G. M. Clifford, "Attribution of causal relationships between human papillomavirus genotypes and invasive cervical cancer globally: a systematic review of the international literature," The Lancet, vol. 404, no. 10451, pp. 435–444, Aug. 2024, doi: https://doi.org/10.1016/s0140-6736(24)01097-3

[3] R. V. Hewavisenti, J. Arena, C. L. Ahlenstiel, and S. C. Sasson, "Human papillomavirus in the context of immunodeficiency: Mechanisms and the rise of advanced therapies to lower the significant cancer risk linked to it," Frontiers in Immunology, vol. 14 Mar. 2023, doi: https://doi.org/10.3389/fimmu.2023.1112513

[4] M. Pankakoski, T. Sarkeala, A. Anttila, and S. Heinävaara, "Efficacy of Cervical Screening Both Within and Outside a Program—A Case-Control Analysis," Cancers, vol. 14, no. 21, p. 5193, Oct. 2022, doi: https://doi.org/10.3390/cancers14215193

[5] M. Arbyn et al., "Effectiveness and accuracy of HPV mRNA testing in screening for cervical cancer: a systematic review and meta-analysis," The Lancet Oncology, vol. 23, no. 7, pp. 950–960, Jul. 2022, doi: https://doi.org/10.1016/S1470-2045(22)00294-7

[6] Z. Petersen et al., "Obstacles to Adoption of Cervical Cancer Screening Services in low-and-middle-income nations: a Systematic Review," BMC Women's Health, vol. 22, no. 1, Dec. 2022, doi: https://doi.org/10.1186/s12905-022-02043-y

[7] D. Trapani et al., "Worldwide issues and policy responses in managing breast cancer," Cancer Treatment Reviews, vol. 104, p. 102339, Mar. 2022, doi: https://doi.org/10.1016/j.ctrv.2022.102339

[8] A. Esteva et al., "Classification of Skin Cancer at Dermatologist Level Using Deep Neural Networks," Nature, vol. 542, no. 7639, pp. 115–118, Jan. 2017, doi: https://doi.org/10.1038/nature21056

[9] N. Coudray et al., "Deep learning for classification and mutation prediction from histopathology images of non-small cell lung cancer," Nature Medicine, vol. 24, no. 10, pp. 1559–1567, Sep. 2018, doi: https://doi.org/10.1038/s41591-018-0177-5

[10] S. J. Pan and Q. Yang, "Transfer Learning: A Survey," IEEE Transactions on Knowledge and Data Engineering, vol. 22, no. 10, pp. 1345–1359, Oct. 2010, doi: https://doi.org/10.1109/tkde.2009.191

[11] O. Russakovsky et al., "ImageNet Large Scale Visual Recognition Challenge," International Journal of Computer Vision, vol. 115, no. 3, pp. 211–252, Apr. 2015, doi: https://doi.org/10.1007/s11263-015-0816-y

[12] Y. Bengio, P. Lamblin, D. Popovici, H. Larochelle, Layer-wise greedy training of deep networks. Progress in Neural Information Processing Systems 19, 153–160 (2007)

[13] F. A. Spanhol, L. S. Oliveira, C. Petitjean, and L. Heutte, "Classification of breast cancer histopathological images via Convolutional Neural Networks," 2016 International Joint Conference on Neural Networks (IJCNN), Jul. 2016, doi: https://doi.org/10.1109/ijcnn.2016.7727519

[14] V. Chandran et al., "Cervical Cancer Diagnosis Utilizing an Ensemble Deep Learning Network with Colposcopic Images," BioMed Research International, pp. 1–15, May 2021, doi: https://doi.org/10.1155/2021/5584004

[15] X. Jiang, Z. Hu, S. Wang, and Y. Zhang, "Deep Learning in Cancer Diagnosis Using Medical Images," Cancers, vol. 15, no. 14, pp. 3608–3608, Jul. 2023, doi: https://doi.org/10.3390/cancers15143608

[16] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770–778, Jun. 2016, doi: https://doi.org/10.1109/cvpr.2016.90

[17] E. Tzeng, J. Hoffman, K. Saenko, and T. Darrell, "Adversarial Discriminative Domain Adaptation," arXiv (Cornell University), February 2017, doi: https://doi.org/10.48550/arxiv.1702.05464

[18] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," Nature, vol. 521, no. 7553, pp. 436–444, May 2015, doi: https://doi.org/10.1038/nature14539

[19] M. D. Zeiler and R. Fergus, "Understanding and Visualizing Convolutional Networks," Computer Vision – ECCV 2014, vol. 8689, pp. 818–833, 2014, doi: https://doi.org/10.1007/978-3-319-10590-1_53

[20] N. Youneszade, M. Marjani, and C. P. Pei, "Deep Learning for Cervical Cancer Diagnosis: Framework, Prospects, and Existing Research Issues," IEEE Access, vol. 11, pp. 6133–6149, 2023, doi: https://doi.org/10.1109/ACCESS.2023.3235833

[21] T. G. Dietterich, "Ensemble Techniques in Machine Learning," Multiple Classifier Systems, vol. 1857, pp. 1–15, 2000, doi: https://doi.org/10.1007/3-540-45014-9_1

[22] Z.-H. Zhou, Methods of Ensemble. 2025. doi: https://doi.org/10.1201/9781003587774

[23] T. Hastie, R. Tibshirani, and J. Friedman, "Inference and Averaging in Models," Springer statistics series, pp. 261–294, Dec. 2008, doi: https://doi.org/10.1007/978-0-387-84858-7_8

[24] M. Mohi, Abdullah Al Mamun, A. Chakrabarti, Rafid Mostafiz, and Samrat Kumar Dey, "A hybrid feature selection method utilizing ensemble machine learning to forecast cervical cancer," Neuroscience Informatics, vol. 4, no. 3, pp. 100169–100169, Aug. 2024, doi: https://doi.org/10.1016/j.neuri.2024.100169

[25] L. Breiman, "Bagging predictors," *Machine Learning*, vol. 24, no. 2, pp. 123–140, Aug. 1996, Available: https://link.springer.com/article/10.1007/BF00058655

[26] Lior Rokach and O. Maimon, "Data Mining using Decomposition Methods," *Springer eBooks*, pp. 981–998, Jan. 2009, doi: https://doi.org/10.1007/978-0-387-09823-4_51

[27] A. S. Li, A. Iyengar, A. Kundu, and E. Bertino, "Security Transfer Learning: Challenges and Upcoming Directions," arXiv.org, Mar. 01, 2024. https://arxiv.org/abs/2403.00935

[28] M. T. Ahad, B. Song, and Y. Li, "Comparative Analysis of Convolutional Neural Networks, Transfer Learning, and Ensemble Methods for Brain Tumor Classification and Detection," Jan. 2024, doi: https://doi.org/10.2139/ssrn.4828934

[29] L. K. Hansen and P. Salamon, "Ensembles of neural networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 12, no. 10, pp. 993–1001, 1990, doi: https://doi.org/10.1109/34.58871

[30] R. M. Munshi, "New ensemble learning method utilizing SVM-imputed ADASYN characteristics for improved cervical cancer forecasting," PLoS ONE, vol. 19, no. 1, pp. e0296107–e0296107, Jan. 2024, doi: https://doi.org/10.1371/journal.pone.0296107

[31] Turki Aljrees, "Enhancing cervical cancer prediction through KNN imputer and multi-model ensemble learning," PloS One, vol. 19, no. 1, pp. e0295632–e0295632, Jan. 2024, doi: https://doi.org/10.1371/journal.pone.0295632

[32] D. Xue et al., "Utilizing Transfer Learning and Ensemble Learning Methods for the Classification of Cervical Histopathology Images," IEEE Access, vol. 8, pp. 104603–104618, 2020, doi: https://doi.org/10.1109/access.2020.2999816

[33] A. Sharma and R. Parvathi, "Improving Cervical Cancer Classification: Using a Hybrid Deep Learning Method that Combines DenseNet201 and InceptionV3," IEEE Access, vol. 13, pp. 9868–9878, 2025, doi: https://doi.org/10.1109/access.2025.3527677

[34] H. Kaur, R. Sharma, and J. Kaur, "Evaluation of deep transfer learning models for cervical cancer classification using pap smear images," Scientific Reports, vol. 15, no. 1, Jan. 2025, doi: https://doi.org/10.1038/s41598-024-74531-0

[35] S. Dhawan, K. Singh, and M. Arora, "Classification of Cervical Images for Prognostic Evaluation of Cervical Cancer Utilizing Deep Neural Networks with Transfer Learning," EAI Endorsed Transactions on Pervasive Health and Technology, p. 169183, Jul. 2018, doi: https://doi.org/10.4108/eai.12-4-2021.169183

[36] E. Ahishakiye and F. Kanobe, "Enhancing cervical cancer classification via transfer learning with deep Gaussian processes and support vector machines," Discover Artificial Intelligence, vol. 4, no. 1, Oct. 2024, doi: https://doi.org/10.1007/s44163-024-00185-6

[37] R. Alsmariy, G. Healy, and H. Abdelhafez, "Cervical Cancer Prediction through Machine Learning Techniques," International Journal of Advanced Computer Science and Applications, vol. 11, no. 7, 2020, doi: https://doi.org/10.14569/ijacsa.2020.0110723

[38] N. Al Mudawi and A. Alazeb, “A Framework for Forecasting Cervical Cancer Using Machine Learning Techniques,” Sensors, vol. 22, no. 11, pp. 4132, mayo 2022, doi: https://doi.org/10.3390/s22114132

[39] Q. Yin, “The Application of Machine Learning in Cervical Cancer Prediction,” *2021 6th International Conference on Machine Learning Technologies*, Apr. 2021, doi: https://doi.org/10.1145/3468891.3468894

[40] I. Pacal, B. Ozdemir, J. Zeynalov, H. Gasimov, and N. Pacal, “An innovative deep learning model based on CNN-ViT for early detection of skin cancer,” Biomedical Signal Processing and Control, vol. 104, p. 107627, Jan. 2025, doi: https://doi.org/10.1016/j.bspc.2025.107627

[41] A. R. Bhatt, A. Ganatra, and K. Kotecha, “Detection of cervical cancer in whole slide images from pap smears utilizing convNet with transfer learning and progressive resizing,” PeerJ Computer Science, vol. 7, p. e348, Feb. 2021, doi: https://doi.org/10.7717/peerj-cs.348

[42] Md Shahin Ali, Md Maruf Hossain, Moutushi Akter Kona, Kazi Rubaya Nowrin, and Md Khairul Islam, “A classification ensemble method for predicting cervical cancer based on behavioral risk factors,” Healthcare analytics, vol. 5, pp. 100324–100324, Jun. 2024, doi: https://doi.org/10.1016/j.health.2024.100324

[43] R. Ahmed, N. Dahmani, G. Dahy, A. Darwish, and A. Ella Hassanien, “Initial Identification and Classification of Cervical Cancer Cells Employing Smoothing Cross Entropy-Driven Multi-Deep Transfer Learning,” IEEE Access, vol. 12, pp. 157838–157853, 2024, doi: https://doi.org/10.1109/access.2024.3485888

[44] Fatemeh Zabihollahy, A. N. Viswanathan, E. J. Schmidt, and J. Lee, “Complete automation of clinical target volume segmentation in cervical cancer using magnetic resonance imaging with convolutional neural networks,” Journal of Applied Clinical Medical Physics, vol. 23, no. 9, Jul. 2022, doi: https://doi.org/10.1002/acm2.13725

[45] Obuli Sai Naren, “Multi Cancer Dataset,” Doi.org, 2022. https://doi.org/10.34740/KAGGLE/DSV/3415848

[46] H.-C. Shin et al., "Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Frameworks, Dataset Features, and Transfer Learning," IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1285–1298, May 2016, doi: https://doi.org/10.1109/tmi.2016.2528162

[47] Y. Bengio, “Practical Suggestions for Gradient-Driven Training of Deep Models,” Lecture Notes in Computer Science, vol. 7700, pp. 437–478, 2012, doi: https://doi.org/10.1007/978-3-642-35289-8_26

[48] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Deep Convolutional Neural Networks for ImageNet Classification,” Communications of the ACM, vol. 60, no. 6, pp. 84–90, May 2012

[49] K. Sienicki, “Remarks on the Article Entitled ’The Source of Quantum Mechanical Statistics: Perspectives from Studies on Human Language’ (arXiv preprint

arXiv:2407.14924, 2024)," Dec. 2024, doi: https://doi.org/10.20944/preprints202411.2377.v1

211-15-4022

ORIGINALITY REPORT

21%	15%	15%	14%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Abu Hanzala, Tanjila Akter, Md. Sadekur Rahman. "A hybrid approach for cervical cancer detection: Combining D-CNN, transfer learning, and ensemble models", Array, 2025 Publication	4%
2	Submitted to Daffodil International University Student Paper	4%
3	dspace.daffodilvarsity.edu.bd:8080 Internet Source	1%
4	doaj.org Internet Source	1%
5	arxiv.org Internet Source	1%
6	ouci.dntb.gov.ua Internet Source	1%
7	Submitted to University of Leeds Student Paper	<1%
8	Submitted to University of Sydney Student Paper	<1%
9	Submitted to VIT University Student Paper	<1%
10	Submitted to University of North Florida Student Paper	<1%
11	Submitted to University of Stirling Student Paper	<1%
12	etasr.com	