COMPUTER VISION WITH ULTRASONOGRAPHY IMAGES ON PREGNANCY STAGES IDENTIFICATION WITH DEEP LEARNING

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APPROVAL

This Project titled "**Computer Vision With Ultrasonography Images On Pregnancy Stages Identification With Deep Learning**" submitted by Jui Saha ID: 201-15-14115 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 10 January 2024.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Sharun Akter Khushbu, Lecturer (Senior Scale), Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

The classification of pregnancy stages is crucial in the field of obstetrics, as identifying the distinct trimesters is beneficial for medical research, prenatal care, and healthcare practices. This study focused on the innovative connection between computer vision and maternal healthcare, specifically using deep learning to automate the identification and classification of stages of pregnancy through ultrasonography images. The study incorporates a fine pre-processing, including normalization, resizing, noise reduction, and augmentation techniques to enhance the robustness of the dataset. This investigation delves into the efficacy of prominent deep learning models VGG16, VGG19, ResNet50, DenseNet, InceptionV3, and Xception utilizing a carefully curated repository of 1,350 images representing various trimesters. The study provides insights into their performance in the context of trimester-specific image analysis. The models' performance metrics reveal noteworthy accuracies: VGG16 (0.94), VGG19 (0.96), ResNet50 (0.95), DenseNet (0.77), InceptionV3 (0.57), and Xception (0.75). These results underscore the varying capabilities of each model in pregnancy stage identification. Remarkably, VGG19 stands out as the leading performer, achieving an accuracy of 0.96, outperforming the other models. Furthermore, our study gains significance by assessing its performance relative to previous research. We evaluate the effectiveness of our approach in comparison to existing methods. Our paper not only introduces a fresh technique for identifying pregnancy stages using a computer but also demonstrates its superiority or equivalency to current practices.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The journey of pregnancy, a complex and remarkable biological process, necessitates vigilant monitoring to ensure the optimal health of both the expectant mother and the developing fetus. Accurate identification of pregnancy stages is crucial for healthcare practitioners, enabling tailored care, anticipation of complications, and timely interventions.

Traditional methods for determining pregnancy stages, including clinical examinations and biochemical tests, though widely used, are not without limitations. Clinical examinations can be subjective, relying on the experience of healthcare professionals, while biochemical tests may introduce invasiveness and errors. These limitations underscore the need for an advanced and objective approach to pregnancy stage identification.

In recent years, ultrasound imaging has emerged as a cornerstone in prenatal care, providing a safe, non-invasive, and widely accessible means of visualizing the developing fetus. The richness of information conveyed by ultrasonography images is invaluable for assessing fetal growth, detecting abnormalities, and monitoring maternal-fetal well-being.

Amidst this backdrop, the potential of computer vision and deep learning technologies becomes evident. These transformative tools, successful in various image analysis tasks, offer automated, efficient, and objective solutions in medical imaging. Healthcare, driven by technological advancements, witnesses unprecedented transformations, particularly in the synergy of computer vision and medical imaging.

This research aims to contribute to this evolving landscape by focusing on the intersection of computer vision and maternal healthcare. Specifically, the task at hand involves the accurate identification of pregnancy stages through the analysis of ultrasonography images.

The significance of accurately determining pregnancy stages cannot be overstated, playing a pivotal role in guiding personalized care, monitoring fetal development, identifying complications, and ensuring the overall well-being of both the expectant mother and the unborn child. Traditionally reliant on subjective assessments and manual measurements, this process is time-consuming and susceptible to inter-observer variability.

In response to these challenges, the adoption of deep learning methodologies emerges as a promising avenue to improve the efficiency and accuracy of pregnancy stage identification. Deep learning algorithms, with their ability to learn intricate patterns from large datasets, are poised to revolutionize the nuanced analysis of ultrasonography images for pregnancy stage classification. This research endeavors to harness the power of deep learning, aiming to develop a robust and reliable computer vision system tailored for this critical task.

1.2 Motivation

The motivation behind this research stems from the pressing need to enhance the accuracy and accessibility of tools employed in maternal healthcare. With the increasing reliance on medical imaging for diagnostic purposes, there is a growing demand for automated and reliable solutions that can augment the capabilities of healthcare practitioners. The motivation is rooted in the belief that the integration of deep learning techniques into pregnancy stage identification can lead to more timely and precise interventions, ultimately improving outcomes for expectant mothers and their children.

1.3 Rationale of the Study

The choice to embark on this study is motivated by the unique challenges associated with the analysis of ultrasonography images for pregnancy stage identification. These challenges include the inherent variability in fetal presentations, the presence of noise and artifacts in the images, and the need for robust algorithms capable of generalizing across diverse datasets. By addressing these challenges, the research aims to contribute valuable insights to the broader field of medical image analysis and provide a foundation for future advancements in computer-aided diagnosis in obstetrics.

1.4 Research Questions

- What is the number of ultrasound images collected in pregnancy detection?
- Where did you get the training and test dataset sources for pregnancy detection through

ultrasonography images?

- How do computer vision algorithms perform to detect pregnancy-related features in ultrasonography images?
- Can transfer learning improve accuracy in pregnancy detection by ultrasonography images?
- How does transfer learning compare to traditional machine learning in pregnancy detection?
- What are the best pre-trained models for transfer learning in pregnancy detection?
- What is the applicability of the proposed deep learning model in clinical settings for early detection and treatment of pregnancy-related conditions?

1.5 Expected Output

- Developing and optimizing a deep learning model for automatic, accurate, and non-invasive pregnancy stage classification from ultrasound images.
- Identifying the optimal transfer learning approach for high-performance pregnancy stage prediction.
- Achieve reliable trimester-level (1st, 2nd, 3rd) pregnancy classification and identification with robust image labeling.
- Enabling cost-effective prenatal care through non-invasive ultrasound analysis, especially in resource-limited settings.
- Significantly improving the accuracy and efficiency of pregnancy stage detection for timely intervention and better healthcare decisions.
- Extracting valuable insights into fetal development and potential complications through data-driven analysis of ultrasound images.
- Advancing deep learning applications in medical diagnosis and image analysis through this automated pregnancy stage detection system.

1.6 Project Management and Finance

In starting my project, the first important step involved the careful data collection. Obtaining accurate ultrasonography images requires the acquisition of appropriate equipment, thus potentially requiring financial assistance. Visits to medical facilities and collaboration with professionals are essential to create a comprehensive dataset.

The next phase involves the development of a robust deep learning model. Which makes it essential to take advantage of platforms like Google Colab to build efficient models. To ensure greater accessibility and reliability for the medical field, premium Google Colab access and consideration for additional funding may be essential.

Project management plays an important role in adapting work related to ultrasonography image analysis. Project success depends on effective planning, coordination and resource allocation. Managing a large dataset of pregnancy-related images requires meticulous organization and strategic planning.

Creating timelines, defining milestones and monitoring progress will be integral to completing the research within the stipulated time frame. Financial management, an important component, involves budgeting and cost control throughout the project life cycle. This includes securing funding for the necessary hardware, software resources, data collection costs, model development and optimization processes.

In summary, coordination between project management and finance is essential for the successful execution of my thesis on "Computer vision with ultrasonography images in pregnancy stages identification with deep learning".

1.7 Report Layout

There is a total of six chapters in my report writing. I have an overview of the entire project.

- In first chapter several sections like 1.1- Introduction, 1.2- Objective, 1.3- Motivation, 1.4- Reasons behind the study, 1.5-Research Questions, 1.6- Expected Outcome, 1.7- Report layout.
- The second chapter are the discussion sections,2.1- Preliminaries/Terminologies, 2.2- Related Works, 2.3- Comparative Analysis and Summary, 2.4 - Scope of the Problem, 2.5- Challenges.

- In the third chapter research method, including 3.1 - Research subject and intermediary,3.2-Data collection Procedure/Dataset Utilized, 3.3 - Statistical Analysis, 3.4 - Proposed Methodology/Applied Mechanism, 3.5- Implementation Requirements.
- In the fourth part chapter Experimental Results and Discussion are covered by the 4.1 Experimental Setup, 4.2-Experimental Results & Analysis,4.3-Discussion.
- In the fifth chapter discusses the Impact on Society, Environment and Sustainability which includes the 5.1-Impact on Society.5.2Impact on Environment.5.3Ethical Aspects,5.4-Sustainability Plan.
- In the last chapter 6: 6.1Summary of the Study,6.2Conclusions,6.3Implication for Further Study.

CHAPTER 2

BACKGROUND STUDY

2.1 Preliminaries

In the exploration of “Computer vision with ultrasonography images on pregnancy identification with deep learning” this section establishes foundational elements for the research endeavor. The preliminary activities encompass a comprehensive literature review to assimilate pertinent knowledge, procurement, and organization of a diverse dataset consisting of ultrasonography images related to pregnancy. The selection and optimization of deep learning models tailored for pregnancy identification are pivotal components, ensuring the robustness and accuracy of the subsequent analysis.

Additionally, the establishment of a structured project management framework is outlined to facilitate seamless progress. Ethical considerations are acknowledged and addressed to uphold the responsible conduct of research in this sensitive domain. These preparatory actions collectively form the groundwork preceding the main phases of model development and evaluation. The intent is to construct a solid foundation, guaranteeing reliable outcomes in the realm of pregnancy identification through computer vision and deep learning methodologies.

2.2 Related Works

Xue, H.et.al [1] works on the early pregnancy fetal facial ultrasound standard plane-assisted recognition algorithm. Their proposal was to develop a lightweight target detection network for early pregnancy fetal ultrasound standard plane recognition and quality assessment. Therefore, they developed a YOLOV4 target detection algorithm based on the backbone network as GostNet and added the attention process CBAM and CA to backbone and neck structures. The average recognition accuracy for their six structures was 94.16%, the detection speed was 51 fps and the model size were 43.2 MB, which is an 83% reduction compared to the original YOLOV4 model. Also, their standard median sagittal plane accuracy was 97.20%, and the standard retro-nasal triangle the scene accuracy was 99.07%.

Li, X.et.al [2] works on the analyzing the pregnancy status of giant pandas with hierarchical behavioral information. The aim of their system proposal was an end-to-end intelligent system to predict the pregnancy status of giant pandas and their expected delivery date (EDD). They first introduced expert knowledge in machine learning methods to solve this problem, thereby significantly improving prediction accuracy. They are collected more than 1700 h of videos from 13 giant pandas (4 pregnant). Their system achieved 91.5% accuracy for pregnancy diagnosis and an average error of 0.579 days for EDD prediction when the observation period was 5 days. Their automated system significantly reduces the need for human intervention, while also minimizing disruption to the pandas' daily lives. Their system has the potential to contribute to the health and genetic diversity of giant pandas, as well as aid in panda artificial breeding and population growth.

He, H.et.al [3] focus on B-Ultrasound Image Analysis of Intrauterine Pregnancy Residues after Mid-Term Pregnancy Based on Smart Medical Big Data. Their main objective is to investigate the diagnostic value of abdominal B-ultrasound images in detecting tissue remnants of intrauterine pregnancy. To address this gap, the paper proposes a CNN model optimization method based on grid search. The optimized CNN model demonstrates impressive accuracy, exceeding 92% in classifying abdominal B-ultrasound images of intrauterine pregnancy tissue residues. The outlining avenues for future investigations to enhance the practical impact of these advancements.

Lin, Q.et.al [4] mention the how much can AI see in early pregnancy: A multi-center study of fetus head characterization in week 10–14 in ultrasound using deep learning. The main purpose of this paper is to investigate whether artificial intelligence can identify fetal intracranial structures at 10-14 weeks of gestation. To provide an automated method for standard and non-standard sagittal view classification in obstetric ultrasound examinations. In this paper 1684 (fetus framework for training and testing 1528 + 156 work with ultrasound images for S-NS classification tests). The FF achieved an AUC of 0.996 in internal testing, indicating a very high level of discrimination between positive and negative examples. Similarly, in external tests, Embryo Framework reached an AUC of 0.974, while other classic deep learning models (ResNet -50=0.883, Xception=0.899, DenseNet -121=0.894) achieved slightly lower AUC values, indicating slightly lower discriminative performance than the FF.

Gupta, K.et.al [5] shows ultrasound placental image texture analysis using artificial intelligence to predict hypertension in pregnancy. Comparison of placental quantitative ultrasound image texture findings in women with HDP (hypertensive disorder of pregnancy) with placental volume in normal women. Of the 429 cases, 58 had HDP (13.5%) that were followed up to delivery. For this paper, the "Resnext 101_32x8d" model was used. which had an accuracy score of 0.710 (good) and a Cohen Kappa score of 0.413 (moderate). In HDP pregnancy, the sensitivity and specificity of first trimester (70.6% & 76.6%) were the best. Moreover, the sensitivity and specificity of 2nd trimester and 3rd trimester were (60.4%,73.3%) & (60.3%,50.7%).

Mu, Y.et.al [6] applying deep learning for adverse pregnancy outcome detection with pre-pregnancy health data. They developed a deep learning algorithm that able to detect and classify adverse pregnancy outcomes before the parents become pregnant. Also, they implemented the proposed deep learning model for adverse pregnancy with 75542 sample of images. Detected and classified outcomes using TensorFlow 0.12.1 with base learning rate of 0.025 and batch size 10 was set. Their proposed model had accuracy 0.892, recall 0.668, F1 score 0.670.

Kim, B.et.al [7] focus on machine learning based automatic identification of fetal abdominal circumference from ultrasound images. This paper proposes a method for automatic fetal biometry estimation from 2D ultrasound data through different processes consisting of CNN and U-Net, one specifically designed for each process. These machine learning techniques take into account clinicians' decisions, anatomical structures, and features of ultrasound images. CNN is used to classify ultrasound images and perform a Hough transform to obtain an initial estimate of AC. The method proposed in this paper is clinically validated Their method achieved an accuracy of 87.10% for AC measurement using a dice similarity metric and a standard plane acceptance test of the fetal abdomen.

Xie, H. N.et.al [8] using deep-learning algorithms to classify fetal brain ultrasound images as normal or abnormal. In this paper they collected 15,372 normal and 14,047 abnormal fetal brain images. They split the data into approximately 80 and 20. The overall deep learning algorithm accuracy was 96.3%.

Looney, P.et.al [9] automatic 3D ultrasound segmentation of the first trimester placenta using deep learning. In this study, they proposed a fully automated placental segmentation method using DeepMedic, a deep convolutional neural network (CNN) trained with the output of a semi-automated random walker method. The method was validated on 300 first-trimester 3D ultrasound scans. Compared to semi-automated segmentation, CNN achieved a median Dice similarity coefficient of 0.73 and a median Hausdorff distance of 27 mm. This marks the first attempt to employ a deep CNN for placental segmentation and demonstrates promising results that could lay the foundation for fully automated segmentation methods. Future research aims to further refine this model and address potential limitations for improved clinical applicability.

Chen, Z.et.al [23] review on artificial intelligence in obstetric ultrasound: an update and future applications. This review paper describes how artificial intelligence (AI) improves image capture, quantification, segmentation, and location identification to improve obstetric ultrasound diagnosis. It also covers some of the difficulties and potential applications of AI in obstetric ultrasound.

2.3 Comparative Analysis and Summary

Study Title & Authors	**Objective/ Purpose**	**Methodologies/ Techniques**	**Key findings / Results**
Xue, H.et.al [1]	Develop a lightweight target detection network for early pregnancy fetal ultrasound standard plane recognition and quality assessment.	YOLOV4 target detection algorithm based on GostNet with CBAM and CA.	Average recognition accuracy of 94.16%, detection speed of 51 fps, model size reduction by 83%. Standard median sagittal plane accuracy of 97.20%, and standard retro-nasal triangle scene accuracy of 99.07%.
Li, X.et.al [2]	Predict pregnancy	Integration of expert	Achieved 91.5%

	status and expected delivery date of giant pandas using an end-to-end intelligent system.	knowledge in machine learning methods. Collection of over 1700 h of videos from 13 giant pandas.	accuracy for pregnancy diagnosis, an average error of 0.579 days for EDD prediction, reducing the need for human intervention. Potential contribution to giant panda health, genetic diversity, and artificial breeding.
He, H.et.al [3]	Investigate the diagnostic value of abdominal B-ultrasound images in detecting tissue remnants of intrauterine pregnancy.	Optimization of CNN model based on grid search.	Optimized CNN model achieved over 92% accuracy in classifying abdominal B-ultrasound images of intrauterine pregnancy tissue residues.
Lin, Q.et.al [4]	Investigate the AI's ability to identify fetal intracranial structures at 10-14 weeks of gestation in obstetric ultrasound examinations.	Use of a framework for training and testing with 1684 ultrasound images.	FF achieved AUC of 0.996 in internal testing, Embryo Framework reached AUC of 0.974 in external tests. Outperformed classic deep learning models like ResNet-50, Xception, DenseNet-

			121.
Gupta, K.et.al [5]	Use artificial intelligence to analyze placental ultrasound images for predicting hypertension in pregnancy.	Utilization of the "Resnext 101_32x8d" model for placental texture analysis.	Achieved an accuracy score of 0.710, Cohen Kappa score of 0.413. Sensitivity and specificity varied across trimesters in hypertensive disorder of pregnancy (HDP).
Mu, Y.et.al [6]	Develop a deep learning algorithm to detect and classify adverse pregnancy outcomes using pre-pregnancy health data.	Implementation of a deep learning model with TensorFlow.	Proposed model demonstrated an accuracy of 0.892, recall of 0.668, and F1 score of 0.670 for adverse pregnancy outcome detection.
Kim, B.et.al [7]	Propose a method for automatic fetal biometry estimation from 2D ultrasound data using CNN and U-Net.	Clinical validation of the method for abdominal circumference (AC) measurement.	Method achieved an accuracy of 87.10% for AC measurement, considering clinicians' decisions and anatomical features.
Xie, H.N.et.al [8]	Use deep-learning algorithms to classify fetal brain ultrasound images as normal or abnormal.	Collection of 15,372 normal and 14,047 abnormal fetal brain images.	Overall deep learning algorithm accuracy of 96.3% in classifying fetal brain ultrasound images.
Looney, P.et.al [9]	Propose a fully automated placental	Utilization of DeepMedic, a deep	CNN achieved a median Dice

	segmentation method using DeepMedic for 3D ultrasound scans.	CNN, trained with semi-automated random walker method.	similarity coefficient of 0.73 and a median Hausdorff distance of 27 mm, showing promise for fully automated placental segmentation.
Chen, Z.et.al [23]	Review the applications of AI in obstetric ultrasound, focusing on improving image capture, quantification, segmentation, and location identification.	Descriptive review of AI's impact on image-related aspects in obstetric ultrasound.	Highlights the improvement of image-related processes in obstetric ultrasound diagnosis through AI.

Table 1: Comparative Analysis on Previous Work

2.4 Scope of the Problem

- This study classifies the stages based on the ultrasonography images. A total of 1350 stages of ultrasonography show different types of pregnancy by real time images.
- A variety of deep learning architectures, such as VGG16, VGG19, ResNet50, DenseNet, Inception V3 and Xception are used to identify the most effective models for classification. Where VGG 19 shows the best performance.
- Data privacy and usage restrictions are ethically covered. In this case doctor and patient permission was highest.
- The results of the study show achievements, limitations and future possibilities.

2.5 Challenges

- Ultrasonography images present challenges due to variations in angles, resolutions, and fetal positions.
- Fetal features' ambiguity in ultrasound images can lead to difficulties in differentiation.
- A limited dataset may impact the model's ability to generalize across diverse pregnancy conditions.
- Annotation complexity in ultrasound images requires meticulous attention to detail for precise labeling.
- Model selection and optimization involve iterative processes for effective pregnancy identification.
- Training and testing deep learning models demand substantial computational resources.
- Interpretability challenges arise from the inherent complexity of deep learning models.
- Extending model accuracy to diverse pregnancy cases poses a generalization challenge.
- Ethical concerns include permissions, handling sensitive medical data, and ethical dataset use.
- Research depth in computer vision with ultrasonography images may be constrained by time and resources.

CHAPTER 3

REASEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

The focal point of this research lies in leveraging advanced computer vision techniques for the precise identification of pregnancy stages through the analysis of ultrasonography images. The study strategically utilizes a meticulously curated dataset featuring 1,350 images that distinctly represent the phases of pregnancy—1st trimester, 2nd trimester, and 3rd trimester. By employing sophisticated deep-learning models and advanced computer vision techniques, our aim is to construct a robust and precise system capable of autonomously classifying and identifying pregnancy stages based on visual cues. This endeavor not only propels the field of medical image analysis forward but also carries the transformative potential to revolutionize prenatal care. By providing healthcare practitioners with a non-invasive, efficient, and accurate tool, it facilitates timely interventions and well-informed decisions, marking a significant stride towards the enhancement of healthcare practices in obstetrics.

3.2 Data Collection Procedure / Dataset Utilized

This section outlines the meticulous procedure employed for data collection and provides insights into the dataset utilized for the research on pregnancy stage identification through computer vision.

3.2.1 Data Collection

To ensure the flexibility and favor of data collection I took the help of mobile camera. Since this is a medical image, I have collected images from "City Dental Medical College", "Selina Memorial Hospital", "Medical Pathology", "New Sheba". The ultrasonography machine had many types of ultra-images, from which I only collected images related to the stages of pregnancy (1st trimester, 2nd trimester, 3rd trimester). There was a total of 738 raw images to choose from. The dataset aims to encompass diverse fetal presentations, account for different ultrasound modalities (transvaginal and transabdominal), and address potential noise and artifacts.

1st Trimester 2nd Trimester 3rd Trimester

Figure 1: Sample of the Dataset

3.2.2 Data Preprocessing

To improve the clarity and standardize features, pre-processing is applied to collected images. To guarantee consistency and the best possible input for deep learning models, methods like normalization, restoration, noise reduction, and augmentation are used. Images are transformed to (224*224) to resize the data. Then a median filter is applied to those images to remove noise. Next, data augmentation techniques are applied to enhance the raw images. After adding new images, the total number of sample images stands at 1,350.

3.3 Statistical Analysis

This section details the statistical approaches employed to analyze the results and validate the effectiveness of the proposed computer vision and deep learning system for pregnancy stage identification. The statistical analyses encompass various aspects of model performance. The accuracy, precision, recall, and F1 score are the assessment metrics that are used to evaluate the performance of the deep learning model.

3.4 Proposed Methodology/Applied Mechanism

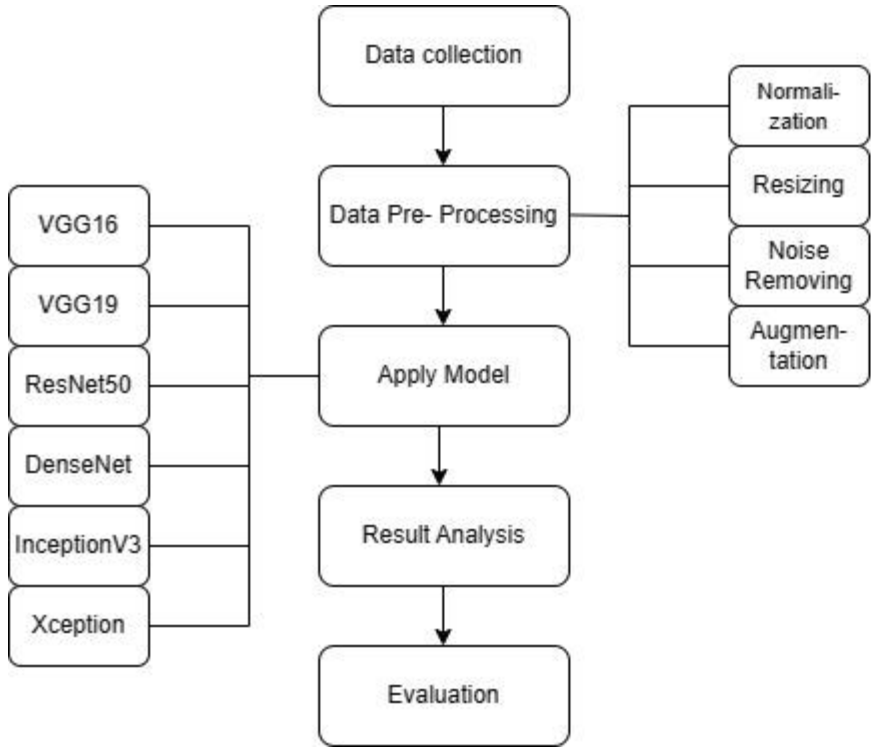

Figure 2: Methodology Diagram

In this part, I applied five steps. These are data collection, data preprocessing, appliedalgorithm, result analysis, and the last one is evaluation.

3.5 Implementation Requirements

- Used Google Colab and TensorFlow to implement the code in a static Internet environment.
- Hardware compatibility and sufficient computational resources are ensured for efficient model execution.
- Python libraries required for data manipulation and visualization are employed in the Google Colab environment.

- Expanded dataset with additional ultrasound images to overcome limitations and increase diversity.
- Data preprocessing techniques are applied, including normalization, resizing, noise reduction, and augmentation.
- Models including VGG16, VGG19, ResNet50, DenseNet, InceptionV3 and Xception are selected for pregnancy classification accuracy.
- Thorough clinical validation has been conducted with healthcare professionals to ensure real-world effectiveness.
- By systematically analyzing and interpreting the model results, their accuracy in quarter detection has been assessed.
- Ensuring scalability for future dataset growth and flexibility for updates to improve model performance.
- Maintained extensive documentation including code comments, resolution of challenges and adherence to ethical guidelines in handling medical data.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION RESULTS

4.1 Experimental Setup

For classification the stages I used TensorFlow to complete the task. Those values are same in every model implementation. Including the number of epochs, batch size, image size, number of layers etc. We train the model via Google Colab with the runtime type is Python 3 and the Hardware accelerator is T4 GPU. Also, use the optimizing function is Adam and activation function are SoftMax. Value of parameter are-

Parameter Value	Value
Number of Epoch	10
Batch size 64	32
Image size	224
Number of layers	3

Table 2: Values of Parameter

4.2 Experimental Results & Analysis

Well, as we know that 100% model accuracy is not possible. By any chance, if the accuracy of the model is 100% then that model is not working properly. That means the model is overfitting. The experimental evaluation involved deploying five distinct models—VGG16, VGG19, ResNet50, DenseNet, InceptionV3, and Xception—along with a hybrid model combining VGG19 and ResNet50. Each model underwent training with an equal number of epochs=10.

Model	Training	Testing	Specification	Sensitivity
VGG16(93.75)	0.9914	0.9312	0.96875	0.9375
VGG19(96.25)	0.9722	0.9563	0.98125	0.9625
ResNet50(95)	0.9872	0.9500	0.975	0.95
DenseNet(77.5)	0.7527	0.7688	0.8875	0.775
InceptionV3(58.75)	0.6360	0.6125	0.79375	0.5875
Xception(75)	0.7066	0.7500	0.875	0.75

Table 3: Image Size of 224*224

Model	Training	Testing	Specification	Sensitivity
VGG16(92.50)	0.9797	0.9062	0.9625	0.925
VGG19(93.75)	0.9636	0.9000	0.96875	0.9375
ResNet50(91.25)	0.9561	0.9250	0.95625	0.9125
DenseNet(72.5)	0.7580	0.7563	0.8625	0.725
InceptionV3 (62.5)	0.6006	0.6125	0.8125	0.625
Xception(81.25)	0.7537	0.7312	0.90625	0.8125

Table 4: Image Size of 256*256

At first comprised the different types of image sizes to identify which type of image size goes well with my model. Image sizes in VGG16, VGG19, Resnet50 and DensNet 224*224 provide better accuracy than sizes of 256*256.

VGG16: In the initial assessment of the VGG16 model, crucial metrics such as Precision, Recall, and F1 Score were computed to analyze the classification outcomes. These metrics play a pivotal role in evaluating the model's performance accuracy.

Class	Precision	Recall	F1-Score
1st Trimester	0.96	1	0.98
2nd Trimester	0.97	0.88	0.92
3rd Trimester	0.89	0.96	0.93
Accuracy			0.94

Table 5: VGG16 Classification Report

These metrics are presented for three different trimesters. For the 1st Trimester, the Precision is 0.96, Recall is 1, and F1-Score is 0.98. For the 2nd Trimester, the Precision is 0.97, Recall is 0.88, and F1-Score is 0.92. Lastly, for the 3rd Trimester, the Precision is 0.89, Recall is 0.96, and F1-Score is 0.93. The overall accuracy achieved by the VGG16 model is 0.94.

VGG19: In the VGG19 model, crucial metrics such as Precision, Recall, and F1 Score were computed to analyze the classification outcomes. These metrics play a pivotal role in evaluating the model's performance accuracy.

Class	Precision	Recall	F1-Score
1st Trimester	1	0.96	0.98
2nd Trimester	0.92	0.96	0.94
3rd Trimester	0.97	0.97	0.97
Accuracy			0.96

Table 6: VGG19 Classification Report

These metrics are presented for three different trimesters. For the 1st Trimester, the Precision is 1, Recall is 0.96, and F1-Score is 0.98. For the 2nd Trimester, the Precision is 0.92, Recall is 0.96, and F1-Score is 0.94. Lastly, for the 3rd Trimester, the Precision is 0.97, Recall is 0.97, and F1-Score is 0.97. The overall accuracy achieved by the VGG19 model is 0.96.

ResNet50: In the ResNet50 model, crucial metrics such as Precision, Recall, and F1 Score were computed to analyze the classification outcomes. These metrics play a pivotal role in evaluating the model's performance accuracy.

Class	**Precision**	**Recall**	**F1-Score**
1st Trimester	0.96	0.92	0.94
2nd Trimester	0.95	0.95	0.95
3rd Trimester	0.94	0.97	0.95
Accuracy			0.95

Table 7: ResNet50 Classification Report

These metrics are presented for three different trimesters. For the 1st Trimester, the Precision is 0.96, Recall is 0.92, and F1-Score is 0.94. For the 2nd Trimester, the Precision is 0.95, Recall is 0.95, and F1-Score is 0.95. Lastly, for the 3rd Trimester, the Precision is 0.94, Recall is 0.97, and F1-Score is 0.95. The overall accuracy achieved by the ResNet50 model is 0.95.

DenseNet: In the initial assessment of the DenseNet model, crucial metrics such as Precision, Recall, and F1 Score were computed to analyze the classification outcomes. These metrics play a pivotal role in evaluating the model's performance accuracy.

Class	Precision	Recall	F1-Score
1st Trimester	0.74	1	0.85
2nd Trimester	1	0.53	0.69
3rd Trimester	0.68	0.86	0.76
Accuracy			0.77

Table 8: DenseNet Classification Report

These metrics are presented for three different trimesters. For the 1st Trimester, the Precision is 0.74, Recall is 1, and F1-Score is 0.85. For the 2nd Trimester, the Precision is 1, Recall is 0.53, and F1-Score is 0.69. Lastly, for the 3rd Trimester, the Precision is 0.68, Recall is 0.86, and F1-Score is 0.76. The overall accuracy achieved by the DenseNet model is 0.77.

InceptionV3: In the initial assessment of the InceptionV3 model, crucial metrics such as Precision, Recall, and F1 Score were computed to analyze the classification outcomes. These metrics play a pivotal role in evaluating the model's performance accuracy.

Class	Precision	Recall	F1-Score
1st Trimester	0.77	0.65	0.70
2nd Trimester	0.30	0.37	0.34
3rd Trimester	0.65	0.67	0.66
Accuracy			0.57

Table 9: InceptionV3 Classification Report

These metrics are presented for three different trimesters. For the 1st Trimester, the Precision is 0.77, Recall is 0.65, and F1-Score is 0.70. For the 2nd Trimester, the Precision is 0.30, Recall is 0.37, and F1-Score is 0.34. Lastly, for the 3rd Trimester, the Precision is 0.65, Recall is 0.67, and F1-Score is 0.66. The overall accuracy achieved by the InceptionV3 model is 0.57.

Xception: In the initial assessment of the Xception model, crucial metrics such as Precision, Recall, and F1 Score were computed to analyze the classification outcomes. These metrics play a pivotal role in evaluating the model's performance accuracy.

Class	**Precision**	**Recall**	**F1-Score**
1st Trimester	0.75	0.76	0.76
2nd Trimester	0.73	0.76	0.75
3rd Trimester	0.77	0.73	0.75
Accuracy			0.75

Table 10: Xception Classification Report

These metrics are presented for three different trimesters. For the 1st Trimester, the Precision is 0.75, Recall is 0.76, and F1-Score is 0.76. For the 2nd Trimester, the Precision is 0.73, Recall is 0.76, and F1-Score is 0.75. Lastly, for the 3rd Trimester, the Precision is 0.77, Recall is 0.73, and F1-Score is 0.75. The overall accuracy achieved by the Xception model is 0.75.

Model/Algorithms	**Accuracy**
VGG16	0.94
VGG19	0.96
ResNet50	0.95

DenseNet	0.77
InceptionV3	0.57
Xception	0.75

Table 11: Comparison Classification Report

After analyzing all the algorithms/ models, we have come to know which algorithms/ models are best for our dataset. We have applied five distinct models—VGG16, VGG19, ResNet50, InceptionV3, and Xception. After comparing among those algorithms, we got that VGG19 delivered the best results, and the accuracy according to the table is 0.96. ResNet50 and VGG16 are comparatively better because their accuracy is 0.95 and 0.94 which is less than the VGG19 model. DenseNet and Xception model are average results and the accuracy is 0.77 and 0.75. Lastly, InceptionV3 made us disappointed hence those results are below acceptable. By implementing them, we got an accuracy of around 0.57. So VGG19 is best for our pregnancy stage identification.

4.3 Discussion

Let's discuss the best performing model which is the VGG19 model. In the 1st trimester, precision correctly predicts all positive cases, and captures 96% of true positive recall. The F1-Score, which balances the precision and recall, increased to an impressive 98%. In the 2nd Trimester, our model demonstrated robust performance, where 92% precision, 96% recall, and a noteworthy F1-Score of 94%. As for the last 3rd Trimester, the model continued its impressive run with 97% precision, 97% recall, and a strong F1-Score of 97%. Overall, the model secured a solid accuracy of 96%, showcasing its proficiency in identifying pregnancy stages across the spectrum. This discussion underscores the VGG19 model’s reliability in accurately discerning pregnancy stages in ultrasonography images.

Configuration No	Batch Size	Accuracy	Miss Class	Findings
1	16	90.97%	9.03	Intermediate Accuracy
2	**32**	**96.25%**	**3.75**	**Highest Accuracy**
3	64	93.75	6.25	Modest Accuracy
4	128	84.38	15.62	Lowest Accuracy

Table 12: Changing the Batch Size

When we use a batch size of 32 it provides the highest accuracy compared to other batch sizes.

Epoch	Loss	Accuracy	Val_Loss	Val_Accuracy
Epoch 1	1.3993	0.4775	1.0817	0.5312
Epoch 2	0.7225	0.6927	0.7177	0.6914
Epoch 3	0.5523	0.7687	0.5372	0.7695
Epoch 4	0.4275	0.8340	0.4340	0.8438
Epoch 5	0.3913	0.8576	0.4196	0.8516
Epoch 6	0.3030	0.8951	0.3343	0.8867
Epoch 7	0.2334	0.9304	0.3029	0.9180
Epoch 8	0.1946	0.9529	0.3278	0.8984
Epoch 9	0.1629	0.9679	0.2858	0.9180
Epoch 10	0.1421	0.9722	0.2471	0.9297

Table 13: First 10 Epoch Values

From the loss, accuracy, validation loss, and validation accuracy of the first 10 epoch values, we can see that epoch 1 e training loss was 1.4, training accuracy was 0.48, validation loss was 1.08, and validation accuracy was 0. 53. Again, epoch 10 training loss is 0.14, training accuracy is 0.97, validation loss is 0.25 and validation accuracy is 0.92.

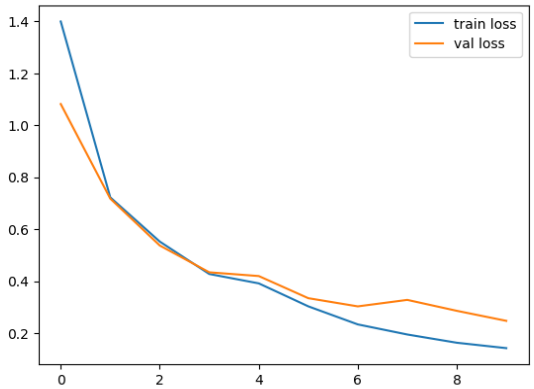

Figure 3: Training vs Validation Loss

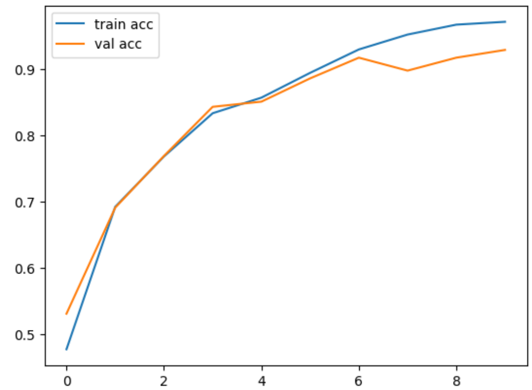

Figure 4: Training vs Validation Accuracy

We see the graphical visualization when the epoch increases, the training loss & validation loss decreases and the training accuracy & validation accuracy increases.

Model	**Class**	**Confusion Matrix**			
		TP	**TN**	**FP**	**FN**
VGG19	1st Trimester	24	55	0	1
	2nd Trimester	23	54	2	1
	3rd Trimester	30	48	1	1

Table 14: Confusion Matrix

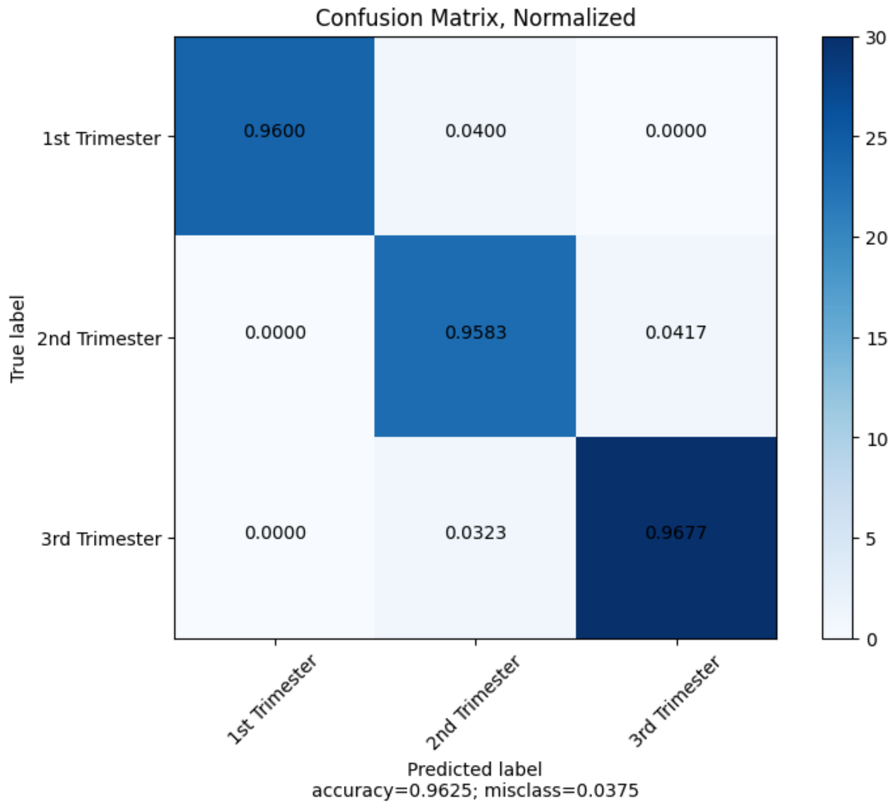

Figure 5: Confusion Matrix

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The impact of my research on society lies in the potential improvements it brings to maternal healthcare through the automated classification of pregnancy. By developing a system dedicated to accurately categorizing pregnancy stages, my work contributes to the well-being of expectant mothers and their infants. This technological advancement can streamline healthcare processes, making them more efficient and accessible, particularly beneficial in resource-limited settings where access to specialized healthcare services is limited. The societal impact is reflected in the potential for enhanced prenatal care, timely interventions, and ultimately, better health outcomes for pregnant individuals and their newborns.

5.2 Impact on Environment

Regarding of my research topic, where the system's purpose is to classify pregnancy stages, it may not have a direct impact on the environment. The focus of the system is on maternal healthcare and the accurate identification of pregnancy stages, contributing more to the medical and healthcare domain than to environmental considerations.

5.3 Ethical Aspects

Ethical considerations in pregnancy stage classification research mainly focus on ensuring patient privacy, consent and responsible use of medical data. During the data collection process, we adhere to ethical aspects by obtaining appropriate permission from the organizations or institutions from which we are collecting data, such as Selina Memorial Hospital. The aim of this system is to improve maternal health care through accurate pregnancy stage classification, and ethical aspects are crucial to protect patient information and maintain the trust of those involved in the health care process. Ethical guidelines and standards are important to ensure the responsible deployment and impact of these systems in healthcare.

5.4 Sustainability Plan

- Optimize the algorithm for energy efficiency to reduce computational resources in pregnancy stages identification.
- Develop responsible data management protocols aligned with ethical standards and privacy considerations.
- Emphasis on environmentally friendly materials and methods in system development and maintenance.
- Advocate for sustainable healthcare practices, integrate systems in an environmentally friendly manner.
- Develop user-friendly guidelines for healthcare professionals promoting water and energy-efficient practices.
- Partner with environmental organizations to support larger conservation initiatives.
- Conduct regular environmental impact assessments to identify areas for improvement.
- Collaborate with experts in sustainable healthcare practices for system development.
- Involve citizens in collecting pregnancy statistics, increase community involvement in sustainability.
- Provide educational resources and promote awareness of the environmental benefits of the system.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

In this paper, everything from data collection to evaluation is done step by step. First, I collected pregnancy-related ultrasonography images from Celina Hospital for data collection. Classification of pregnancy stages is critical in obstetrics. Because **restless** of the baby and mother depends on the trimester. 1350 ultrasonography images have been used in this study. Data has been pre-processed depending on these 1350 images. After finishing the pre-processing techniques apply the different types of model. Results analysis shows that VGG19 stands out as the top performer compared to other models. Whereas VGG19 achieved an accuracy of 0.96 the worst performing model is InceptionV3 with an accuracy of 0.57.

6.2 Conclusions

Classification of pregnancy stages is significant in obstetrics. Because identifying distinct trimesters plays a beneficial role in medical research, prenatal care, and healthcare practice. 1350 ultrasound pictures from the three trimesters of pregnancy were used in this classification. In addition, normalization, resizing, noise reduction, and augmentation techniques were used to increase the robustness of the dataset. In this paper, there are six separate models / algorithms were used to classify those trimesters. Notably, the VGG19 surpasses the other models and stands out as the best performer. In contrast, VGG19 achieved the highest accuracy of 0.96 out of 1.

6.3 Implication for Further Study

- Since the amount of my dataset is very low, I will increase the dataset.
- Hybrid model will be used for pregnancy classification accuracy.
- Conduct a full clinical validation of models.
- After the pregnancy classification, my model should give all the good or bad information of that trimester.

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Appendix

The appendix section in this research paper encompasses essential supplementary information. It includes details on data collection sources and methods, a step-by-step guide to data pre-processing techniques, comprehensive insights into deep learning model architectures, specifics on the experimental setup including parameters for each model, additional results and performance metrics presented in tables and figures, excerpts or links to the codebase used for model development, a discussion on ethical considerations and protocols, copies of surveys or questionnaires if applicable, and any extra figures or tables offering further context or details related to the research. This comprehensive set of appendices enhances the reader's understanding and provides transparency in the research methodology.