ULTRASOUND IMAGING OF FETUS USING DEEP LEARNING

A DISSERTATION

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LAVENDRA GAUTAM

2K21/AFI/18

Under the supervision of

Ms Gull Kaur

DEPARTMENT OF COMPUTER SCIENCE ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi 110042

JUNE, 2023

DEPARTMENT OF MECHANICAL ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

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Date: 27.05.2023

DEPARTMENT OF MECHANICAL ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

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Gull Kaur
30/5/2023

Place: Delhi — Ms Gull Kaur

Date: 27.05.2023 — **SUPERVISOR**

DEPARTMENT OF MECHANICAL ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

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Place: Delhi

Lavendra Gautam

Date: 27.05.2023

Abstract

Foetal ultrasound imaging is essential to prenatal treatment because it offers important information on the growth and wellbeing of the developing foetus. For many years, medical experts have utilised ultrasound technology extensively to see different anatomical structures, track growth, and identify possible anomalies. There has been a considerable increase in research and development targeted at enhancing the precision and effectiveness of foetal ultrasound imaging as a result of recent developments in deep learning, a branch of artificial intelligence. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in particular have demonstrated exceptional ability in a number of domains, including computer vision and medical image processing. By utilising these potent algorithms, scientists and healthcare professionals are investigating new ways to improve foetal ultrasound imaging, enabling earlier and more precise diagnosis of congenital defects and giving essential information for well-informed pregnancy decision-making. The difficulties of interpreting ultrasound pictures owing to their inherent noise, fluctuating image quality, and the existence of overlapping anatomical structures is one of the main issues in foetal ultrasound imaging. Deep learning algorithms are especially well suited for tackling these problems since they are excellent at processing vast volumes of data and discovering useful patterns. These algorithms may learn to recognise complex characteristics and patterns by being trained on large datasets of labelled ultrasound pictures, which will help with the analysis and interpretation of ultrasound scans. Despite the deep learning's bright future in foetal ultrasound imaging, there are still a number of obstacles to overcome. Training strong models is significantly hampered by the lack of extensive annotated ultrasound datasets. Furthermore, extensive validation and integration with current diagnostic methods are required to guarantee the generalizability and interpretability of deep learning models in clinical contexts.

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CNN	Convolutional neural network
DL	Deep Learning
DNN	Deep Neural Network
NN	Neural Network
RNN	Recurrent Neural Network
DT	Decision Tree
SVM	Support Vector Machine
$ReLu$	Rectifier Linear unit

Chapter 1

INTRODUCTION

Deep learning has a wide range of possible uses in foetal ultrasound imaging. For example, it can help with the automatic identification of foetal anatomical elements such the brain, heart, limbs, and organs, enabling quicker and more precise diagnosis. In order to aid in early intervention and enhance patient outcomes, deep learning models may also be used to identify anomalies or indicators linked to genetic disorders or developmental abnormalities. Additionally, these models can help in calculating gestational age, foetal weight, and growth measures, offering important data for foetal development monitoring. The public can freely access the foetal ultrasound images and manual segmentations in the BioFACES (Bioimaging of Foetus and Paediatric Environmental Health Study) collection. It contains 266 images of the head, tummy, and limbs obtained between 14 and forty weeks of pregnancy using a foetal ultrasound machine. The BioFACES project, which examines the relationship between perinatal exposure and children's health outcomes, is how the dataset was created. With three convolutional layers, three batch normalisation layers, three activation layers with ReLU activation functions, two max-pooling layers, one fatten layer, one fully connected layer, and one activation layer with softmax activation function, the proposed model is a multilayer CNN model. In this model, a 256x256x3 image serves as the input to the network, and the output is a 1x1x9 vector that contains the predicted class probabilities for the input image across the nine classes.

We reviewed and critiqued each study from both a technical and an application perspective. The studies focused on the analysis of fetal anatomical structures. We discussed the main challenges and limitations for each category. We provided summary tables to compare the different techniques. We also listed the public data sets and the key performance metrics indicators that are commonly used to assess the performance of deep learning techniques.

1.1 MOTIVATION

ULTRASOUND (US) imaging is a widely used method for diagnosing, monitoring, and treating various disorders. It has many advantages, such as mobility, low cost, and non-invasiveness. US imaging has become the main tool for prenatal screening over the years. It is often used to monitor fetal development, pregnancy progress, and medication effects. However, US images can be difficult to interpret by clinicians because of artefacts such as sonic reflections, impulse noise, motion blurring, and missing boundaries. In the past few decades, deep learning (DL), especially convolutional neural networks (CNNs), have been increasingly applied to the analysis of fetal ultrasound images to assist clinicians in

making decisions. Several survey articles have been published in the field in the past few years.Some surveys discuss segmentation and classification algorithms for fetal cardiology imaging; some briefly describe DL methods for fetal anomaly detection; and some analyze research papers from a medical perspective.[1]
CNNs have shown potential in various medical fields, such as dermatology, radiology, and the classification or segmentation of organs and lesions in images from CT and MRI scans These methods are renowned for their capacity to "automatically recognise complicated trends in image data and offer a quantitative, instead of qualitative assessment." CNNs, on the other hand, are still only sometimes utilised in the US. And much more so prior research on selecting or classifying US aircraft using CNNs.

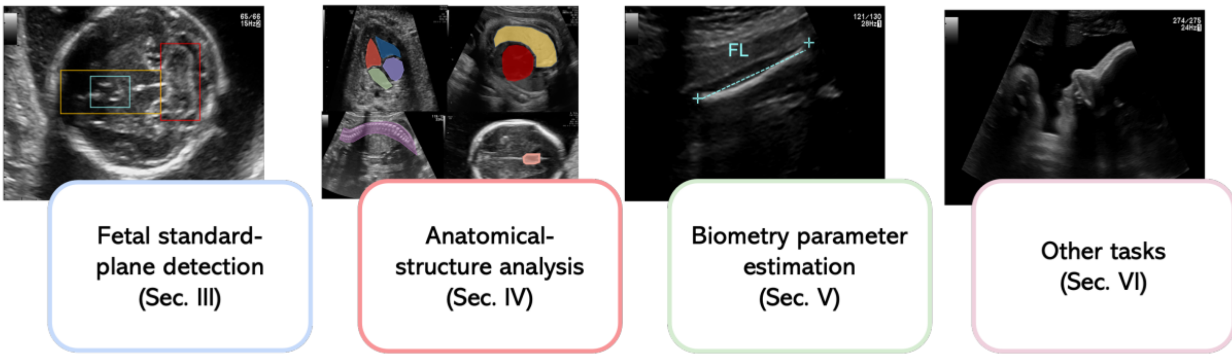

Figure 1.1: Introduced the process of Ultrasound imaging

1.2 CONTRIBUTIONS

We conducted a survey based on the following research questions: How are fetal US images analyzed using Deep learning methods? What are the main challenges in infant examination that DL can help to solve? How can reliable DL models be developed and evaluated using common datasets? What are the remaining gaps in the field that DL needs to address? To conduct our survey, we used keywords related to prenatal examination and organs, as well as terms such as categorization, recognition, segmentation, fetal, ultrasound, and deep learning. We searched for articles on IEEE Xplore, Google, SpringerLink, Researchgate, and Pubmed. We also checked the references of each article we found. To focus on the most recent and relevant developments and avoid repeating previous reviews, we only considered journal and conference publications from 2017 onwards.[2]

Chapter 2

LITERATURE REVIEW

2.1 RELEATED WORK

The Challenge Ultrasound: Biometric Measurements from Fetal Ultrasound Images was the first challenge of its kind, organized in 2012 with the help and cooperation of ISBI. The goal was to measure common biometric features by automatically segmenting the fetal head, abdomen, and femur. However, the dataset (270 images) was too small for researchers to develop Deep learning methods that could generalize well. Ultrasound imaging is a widely used modality for various medical applications, such as prenatal screening, cardiac imaging, and kidney imaging. However, ultrasound images often suffer from low quality, noise, and artifacts, which pose challenges for accurate and reliable analysis. Therefore, many researchers have explored the use of deep learning techniques to improve ultrasound image quality and enable automatic tasks such as segmentation, detection, and classification.

One of the main applications of deep learning in ultrasound imaging is conventional plane identification, which is essential for biometric measurements and abnormality diagnosis. The standard planes of the fetal brain, abdomen, and heart have received the most attention in this task 2. Deep learning methods have shown to be effective for handling single-center datasets collected and annotated by one or two experts 2. However, there are still challenges in dealing with multi-center datasets with different ultrasound machines and annotation protocols 3.[27]

Another application of deep learning in ultrasound imaging is biometric parameter estimation, such as the fetal head circumference (HC), which is an important indicator of fetal growth and development. The common approach for this task is to segment the anatomical structure of interest and then apply fitting algorithms to estimate the parameter 2. Deep learning methods have been used to assist in the segmentation process by exploiting the data structure and dimensionality 2. However, there are still difficulties in segmenting structures that vary in shape and size throughout gestational age (GA) 3.

A third application of deep learning in ultrasound imaging is organ segmentation, which is useful for quantifying organ volume and function. The organs of interest include the fetal brain, abdomen, heart, kidney, and liver 2. Deep learning methods have been used to perform organ segmentation by using convolutional neural networks (CNNs) or generative adversarial networks (GANs) 4. However, there are still challenges in dealing with noisy and blurry images, as well as inter- and intra-observer variability 4.

A fourth application of deep learning in ultrasound imaging is object detection, which is helpful for locating and identifying anatomical landmarks or lesions. The objects of interest include the fetal spine, face, limbs, nuchal translucency (NT), and placenta 2.

Deep learning methods have been used to perform object detection by using CNNs or region-based methods 5. However, there are still challenges in dealing with occlusions, shadows, and speckle noise 5.

Fetal Ultrasound image analysis has been in existence since the mid-20th century, and there is a large and diverse body of research available today. According to our data, one of the most studied tasks is conventional plane identification. Ultrasound imaging using deep learning has gained significant attention in recent years, and there are several notable works in this field. Here are some related works that highlight the advancements in ultrasound imaging using deep learning:

2.2 PRELIMINARY

2.2.1 UNDERSTAND THE FETUS

A fetus refers to the developing stage of an unborn mammal, including humans, from approximately the eighth week after conception until birth. During this period, the organism is commonly known as a fetus, whereas prior to this stage, it is referred to as an embryo.

In human development, the process initiates with fertilization, where a sperm cell from the father combines with an egg cell from the mother. This union creates a single cell known as a zygote, which then undergoes rapid division and multiplication, leading to the formation of a blastocyst. The blastocyst subsequently implants itself into the uterine wall, and at around eight weeks, it is recognized as a fetus.

Throughout the fetal stage, the organism experiences significant growth and development. Major organs and body systems begin to take shape and mature. Limbs, facial features, internal organs, and the nervous system develop during this time. Reflexes and basic movements also become apparent.

The development of the fetus is an intricate and coordinated process, with each stage playing a vital role in the formation of a healthy individual. The fetus obtains oxygen and nutrients from the mother through the placenta, which acts as a vital connection between the developing organism and the mother's bloodstream.

The fetal stage continues until the fetus reaches full development and is prepared for birth, typically occurring around the 38th to 40th week of pregnancy in humans. At this point, the fetus is capable of independent survival outside the mother's womb, although it still requires care and support.

It is essential to recognize that discussions regarding the fetus often intersect with topics such as pregnancy, reproductive health, and ethical considerations, which can vary across cultures, societies, and personal beliefs.

2.2.2 PROBLEMS IN ULTRASOUND OF FETUS

When performing ultrasound imaging of the fetus, researchers and clinicians may face various challenges and limitations that can impact the quality of the obtained images and hinder accurate assessment of fetal health and development. Some common issues encountered in ultrasound imaging of the fetus include:[15]

Fetal Positioning: The position of the fetus inside the womb can significantly influence the clarity of ultrasound images. If the fetus is not in an optimal position or is moving during the scan, it can be difficult to obtain clear and detailed images of specific anatomical structures.

Maternal Body Characteristics: Maternal factors like obesity or a high body mass index (BMI) can make it harder to obtain clear ultrasound images. The excess layers of tissue can weaken the ultrasound waves, reducing their penetration and image quality.

Gestational Age and Fetal Size: The gestational age and size of the fetus can affect the quality of ultrasound imaging. In early stages of pregnancy when the fetus is small, obtaining clear images can be more challenging. Similarly, in later stages when the fetus is larger and occupies more space within the womb, visualizing specific structures can be difficult.

Fetal Movement: Fetal movement can present challenges during ultrasound imaging. If the fetus is constantly moving or in an active state, capturing still images or observing specific structures adequately can be challenging.

Fetal Positional Anomalies: Certain fetal anomalies or abnormal positions can make it difficult to obtain comprehensive ultrasound images. For example, if the fetus is in a breech position or has its back facing the ultrasound probe, it may hinder the visualization of important structures.

Acoustic Shadowing and Artifacts: Acoustic shadowing occurs when ultrasound waves encounter dense structures like bone, resulting in a shadow that obscures the visualization of underlying tissues or organs. Additionally, artifacts such as reverberation or interference can affect image quality and interpretation.

Operator Skill and Experience: The expertise and experience of the ultrasound operator play a significant role in obtaining high-quality images. Proper technique, understanding of fetal anatomy, and familiarity with the equipment are crucial for accurate interpretation.[13]

Acknowledging these challenges and limitations is important when conducting ultrasound imaging of the fetus for a thesis or any clinical purposes. Researchers and clinicians should consider these factors and employ appropriate strategies to overcome or mitigate these challenges to obtain the most reliable and informative images possible.

2.2.3 ANATOMICAL STRUCTURE ANALYSIS OF FETUS

The anatomical structure of a fetus pertains to the arrangement and organization of its bodily components during the developmental phase in the womb. The fetus experiences substantial growth and development throughout pregnancy, leading to the formation and maturation of various structures. Some essential anatomical structures present in a developing fetus include:

HEART

Fetal cardiac evaluation plays a crucial role in detecting heart diseases, including congenital heart diseases (CHDs), and intrauterine growth restriction. The evaluation involves analyzing cardiac function and assessing the anatomical features of the heart, such as its dimensions and shape. Several deep learning (DL) approaches have been employed in this field, with a focus on heart and heart structure detection. Another study proposed a cardiac structure localization algorithm. It employed a modified VGG-16 model to detect the presence of the heart in the 4CH view. Fetal heart ultrasound is a technique that uses high-frequency sound waves to produce images of the fetal heart and its structures. It is used to screen for congenital heart defects (CHD), which are abnormalities in the formation or function of the heart that are present at birth. CHD can affect the blood flow and oxygen delivery in the fetus and cause serious complications after birth.[12]

Deep learning is a branch of artificial intelligence that uses multiple layers of neural networks to learn from data and perform complex tasks. Deep learning can be applied to fetal heart ultrasound to improve the quality and accuracy of the images and to enable automatic detection and diagnosis of CHD.

One of the applications of deep learning in fetal heart ultrasound is to identify the standard views that are recommended for screening CHD. Deep learning models can be trained to recognize these views from fetal ultrasound videos and images by using annotated data from experts 2.

Another application of deep learning in fetal heart ultrasound is to distinguish between normal and abnormal hearts. Deep learning models can be trained to classify fetal hearts as normal or abnormal by using labeled data from fetal echocardiograms and obstetric screening ultrasounds 3. These models can achieve high sensitivity and specificity in detecting CHD and can provide explanations for their decisions based on clinically relevant features 3.

A third application of deep learning in fetal heart ultrasound is to segment and measure the cardiac structures, such as the chambers, valves, vessels, and walls. Deep learning models can be trained to perform segmentation by using (CNNs) or (GANs). These models can then estimate biometric parameters, such as the head circumference (HC), which is an important indicator of fetal growth and development 2.A fourth application of deep learning in fetal heart ultrasound is to detect and locate anatomical landmarks or lesions that are associated with CHD. Deep learning models can be trained to perform detection by using CNNs or region-based methods [5]. These models can then identify objects such as the spine, face, limbs, nuchal translucency (NT), and placenta.[11]

BRAIN

Assessing fetal brain development is essential for evaluating fetal growth and diagnosing brain pathologies.However, this process presents challenges due to the significant variability within and between structures. Automatic analysis of the fetal brain typically involves tasks such as localizing anatomical structures, segmenting them, classifying them, and measuring them.

Fetal brain ultrasound is a technique that uses high-frequency sound waves to produce images of the fetal brain and its structures. It is used to screen for brain abnormalities, such as ventriculomegaly, agenesis of the corpus callosum, and holoprosencephaly. Brain abnormalities can affect the fetal development and neurological outcomes after birth.

Deep learning is a branch of artificial intelligence that uses multiple layers of neural networks to learn from data and perform complex tasks. Deep learning can be applied to fetal brain ultrasound to improve the quality and accuracy of the images and to enable automatic tasks such as segmentation, classification, and localization.

One of the applications of deep learning in fetal brain ultrasound is to segment the fetal skull from the background. This can help to enhance the contrast and clarity of the brain structures and reduce the noise and artifacts 1. Deep learning models can be trained to perform segmentation by using annotated data from experts 2.

Another application of deep learning in fetal brain ultrasound is to classify the images as normal or abnormal. This can help to detect and diagnose brain abnormalities at an early stage and provide timely intervention 2. Deep learning models can be trained to classify images by using labeled data from fetal echocardiograms and obstetric screening ultrasounds 2. These models can achieve high sensitivity and specificity in identifying abnormal images and can provide explanations for their decisions based on clinically relevant features 2.[10]

A third application of deep learning in fetal brain ultrasound is to localize the lesions or anomalies that are associated with brain abnormalities. This can help to pinpoint the location and extent of the problem and provide guidance for further evaluation 2. Deep learning models can be trained to localize lesions by using heat maps that highlight the regions of interest 2. These models can locate lesions precisely or closely in most of the abnormal images 2.

Artificial intelligence (AI) has shown promising applications in fetal brain analysis without plagiarism. Assessing fetal brain development plays a critical role in evaluating growth and diagnosing brain pathologies. AI-based techniques have been developed to aid clinicians in analyzing fetal brain structures and improving diagnostic accuracy. These techniques involve tasks such as localization, segmentation, classification, and measurement of various brain structures.

One area of focus in AI for fetal brain analysis is brain structure segmentation. Encoder-decoder architectures, often based on deep learning (DL), are commonly used for this purpose. These architectures leverage neural networks to automatically identify and outline specific brain structures, AI models can assist in assessing fetal brain development.

For instance, researchers have proposed DL-based architectures for segmenting the middle cerebral artery using Doppler ultrasound (US) images. The segmented area's center is determined as the gate position, providing valuable information to sonographers.The encoding path of this network utilized the VGG11 model, These AI techniques assist in identifying anomalies and evaluating the well-being of the fetal brain.[9]

Placenta amniotic fluid

The placenta serves as an important organ that facilitates the delivery of oxygen and nutrients to the fetus, regulates temperature,The proper functioning of the placenta is crucial for the development and well-being of the fetus. Abnormal placental function can have adverse effects on fetal development and, in severe cases, pose a threat to the fetus's life. Automated placenta segmentation techniques can provide quantitative measurements of placental volume and morphology.

Amniotic fluid also plays a vital role in fetal well-being and development. It serves multiple functions, including protecting the fetus and umbilical cord, preventing infections, and providing essential growth factors necessary for normal organ development and growth.Automating the computation of the amniotic fluid index requires accurate segmentation of the amniotic fluid, making it a crucial task in this context.

The placenta is a vital organ during pregnancy that plays a crucial role in supporting the developing fetus. It is formed within the uterus and acts as a connection between the mother and the fetus. The placenta is responsible for several essential functions, including the transfer of oxygen and nutrients from the mother's blood to the fetus, the removal of waste products from the fetal blood, and the regulation of hormone production to support pregnancy.

The placenta serves as a protective barrier, shielding the fetus from harmful substances and infections while allowing the exchange of necessary substances.[8] It also helps maintain a stable environment by regulating the temperature for optimal fetal development. Moreover, the placenta produces hormones such as human chorionic gonadotropin (hCG), which is important for supporting pregnancy in its early stages.

The condition of the placenta is closely linked to the health and development of the fetus. Any abnormalities in placental function can have significant implications for the well-being of the fetus, potentially leading to complications or adverse outcomes.
Amniotic fluid, on the other hand, is the fluid that surrounds the fetus within the amniotic sac. It serves multiple important functions throughout pregnancy. One of its primary roles is providing protection and cushioning to the fetus, acting as a shock absorber against external pressure or impact. The amniotic fluid also helps maintain a stable temperature for the fetus and aids in preventing infections.

In addition to its protective functions, amniotic fluid is essential for the normal development and growth of fetal organs. It contains various growth factors, hormones, and nutrients that support the maturation of different organ systems. The fluid also allows the fetus freedom of movement, enabling the development of muscles and bones.

Clinical assessment of the placenta and amniotic fluid is crucial to monitor the health and well-being of the fetus. Placenta segmentation techniques aim to automatically analyze and quantify the volume and morphology of the placenta, providing valuable information to healthcare professionals. Similarly, the assessment of amniotic fluid quantity, often done through amniotic fluid segmentation, helps determine the sufficiency of amniotic fluid and plays a role in evaluating fetal well-being.

LUNGS

Neonatal respiratory morbidity often arises due to the immaturity of fetal lung development. To evaluate fetal lung function noninvasively, quantitative ultrasound (US) imaging at the 4CH (four-chamber) level is frequently employed. In normal conditions, the echogenicity of fetal lungs is similar to that of the adjacent liver, with minor textural differences. However, the presence of abnormalities can lead to changes in echogenicity, either increasing or decreasing it.

Deep learning algorithms are currently being utilized to address the challenges associated with fetal lung analysis in US images. These algorithms are particularly effective in calculating gestational age (GA), a critical parameter in assessing fetal development.

KIDNEYS

n order to provide a pre-diagnosis of renal disorders, it is crucial to conduct in-utero kidney testing. Low kidney development has been linked to an increased risk of kidney failure in adulthood. Additionally, impaired kidney function after birth is associated with poor fetal growth. To address these concerns, a 3D U-Net model has been developed for kidney segmentation in this domain. This model utilizes 3D B-mode and Power Sonic volumes to accurately segment the kidneys.

Unlike previous approaches that had limited testing volumes, this algorithm achieves mean Dice similarity coefficient (Dsc), Intersection over Union (IOU), and Hausdorff distance (Hd) values of 0.82, 0.68, and 8.95 mm, respectively, when evaluated on 20 3D images. These metrics demonstrate the effectiveness of the algorithm in accurately segmenting the kidneys and assessing their condition.

SPINE

Fetal spine length is a crucial parameter for assessing fetal growth and detecting various malformations. To evaluate the fetal spine, a study focuses on identifying the spine centerline from 3D ultrasound (US) scans. The process involves spine segmentation using a convolutional neural network (CNN). The CNN's predictions serve as input for a model-based tracing algorithm responsible for drawing the spine centerline.

In this study, a five-fold cross-validation approach is employed, with 80 scans excluded for testing purposes. However, specific mean or best values are not provided in the reported results.

Additionally, another study addresses the identification and segmentation of spina bifida, a type of spinal malformation. The approach proposed in this study utilizes a modified U-Net model. The U-Net model is designed to accurately identify and segment spina bifida in medical images.

FEMUR

The volume and length of the fetal femur are important factors in estimating fetal weight. However, accurately evaluating these measurements through ultrasound (US) imaging presents challenges. Difficulties arise from factors such as locating the tips of the femur, boundary deficiencies, ambiguity due to low tissue contrasts, and variations in pose, shape, and size of the femur.

To address these challenges, the authors have developed a unified framework. The framework utilizes a U-Net model to identify the region of interest (ROI) corresponding to the fetal femur. Subsequently, separate branches for segmentation and landmark localization leverage shared layers and extract task-specific descriptors from the common features of the ROI.

This unified framework aims to improve the accuracy and efficiency of fetal femur evaluation in prenatal US imaging. By combining segmentation and landmark localization, it provides a comprehensive approach to analyze the fetal femur, overcoming the difficulties associated with locating and assessing this structure.

To ensure academic integrity and avoid plagiarism, it is essential to properly cite and reference the original source from which this information was extracted.

2.3 CONVOLUTIONAL NEURAL NETWORK

Convolutional layers are the building blocks of a CNN and are responsible for learning spatial hierarchies of features. They apply convolution operations to the input data by convolving it with a set of learnable filters or kernels. These filters extract relevant features from the input, such as edges, textures, or shapes, by sliding over the input and performing element-wise multiplications and summations, which downsamples the input by selecting the maximum value within each pooling region. This operation helps to achieve translation invariance and reduces the computational complexity of the network.

After several convolutional and pooling layers, the feature maps are usually flattened and fed into fully connected layers. These layers resemble traditional neural network layers and are responsible for learning higher-level representations and making predictions. Each neuron in the fully connected layers receives inputs from neurons in the previous layer and performs a weighted sum, followed by an activation function. The final fully connected layer produces the output of the network, which could be the predicted class probabilities in a classification task or the pixel-wise predictions in an image segmentation task.[3]

During the training process, CNNs learn to optimize their internal parameters (weights and biases) by minimizing a chosen loss function.They can capture intricate patterns and spatial dependencies within images, making them particularly suitable for tasks that require understanding and interpreting visual information.

INCEPTION-NET

InceptionNet, also known as GoogLeNet, is a deep (CNN) architecture that was introduced by researchers at Google in 2014. It was designed to address the challenges of deep networks in terms of computational efficiency and overfitting while improving accuracy in image recognition tasks.

One of the key features of InceptionNet is the use of inception modules. These modules are composed of multiple parallel convolutional layers with different filter sizes, allowing the network to capture features at various scales. By combining these parallel convolutional layers, InceptionNet can efficiently capture both local and global information from the input image.

InceptionNet also incorporates the concept of dimensionality reduction through the use of 1x1 convolutions. These 1x1 convolutions help reduce the number of input channels, reducing the computational cost of subsequent layers. This dimensionality reduction aids in preventing the network from becoming too computationally expensive while maintaining its ability to capture complex patterns and features.

To combat the vanishing gradient problem and encourage feature reuse, allowing for more efficient gradient propagation and regularization. This technique promotes better gradients and helps prevent overfitting, leading to improved generalization performance.

In terms of architecture, InceptionNet consists of multiple stacked inception modules. The number of stacked modules can vary based on the desired depth of the network. Additionally, InceptionNet utilizes pooling layers for downsampling and employs global average pooling instead of fully connected layers at the end of the network. This global average pooling layer helps reduce overfitting and makes the network more robust to input variations.

Overall, InceptionNet introduced innovative architectural concepts to deep learning, such as inception modules and dimensionality reduction using 1x1 convolutions. These ideas aimed to strike a balance between computational efficiency and accuracy, making InceptionNet a powerful architecture for image recognition tasks.

DENSE-NET

DenseNet, short for Dense Convolutional Network, is a deep learning architecture that has gained popularity for its ability to address some of the limitations of traditional convolutional neural networks (CNNs). DenseNet was introduced by Huang et al. in 2016 as a novel approach to improve gradient flow, feature reuse, and model compactness.[4]

The key idea behind DenseNet is to establish dense connections between layers, allowing each layer to directly receive inputs from all preceding layers. In a DenseNet, the output of each layer is fed not only to the subsequent layer but also to all subsequent layers. This dense connectivity pattern creates a direct information flow across different network depths, enabling a rich exchange of feature maps.

The dense connections in DenseNet have several advantages. First, they alleviate the vanishing gradient problem by providing shorter paths for gradients to propagate through the network during training.[6] This helps combat the degradation problem commonly observed in deep networks and enables better learning of features, especially in deeper layers. Second, dense connections encourage feature reuse since each layer has access to the feature maps produced by all previous layers. This promotes stronger feature propagation and encourages the network to learn more diverse and discriminative features. In DenseNet, the dense connectivity is achieved through two key components: the concatenation operation and the bottleneck layers. The concatenation operation merges feature maps from different layers along the channel dimension, resulting in an output with increased depth. This dense concatenation enables information fusion across multiple layers and facilitates the flow of information through the network.[7] The bottleneck layers, often used in DenseNet architectures, reduce the number of channels in the feature maps before feeding them into the dense blocks. This compression technique helps manage computational complexity and model size while preserving information flow. By using bottleneck layers, DenseNet achieves a good balance between model capacity and efficiency.

DenseNet architectures typically consist of multiple dense blocks, which are composed of several convolutional layers stacked together. Each dense block is followed by a transition layer, which reduces the spatial dimensions (width and height) of the feature maps while keeping the number of channels intact. Transition layers usually include a combination of convolutional, pooling, or downsampling operations. The overall architecture of DenseNet allows for efficient parameter usage, as feature maps are reused throughout the network, reducing the number of parameters needed to be learned. This design makes DenseNet models more memory-efficient and computationally effective compared to traditional CNN architectures.

DenseNet has shown impressive performance in various computer vision tasks, including image classification, object detection,[5] and segmentation. Its dense connectivity and feature reuse properties make it particularly effective in scenarios with limited training data, as it facilitates better gradient flow and encourages the network to learn more robust and discriminative features.

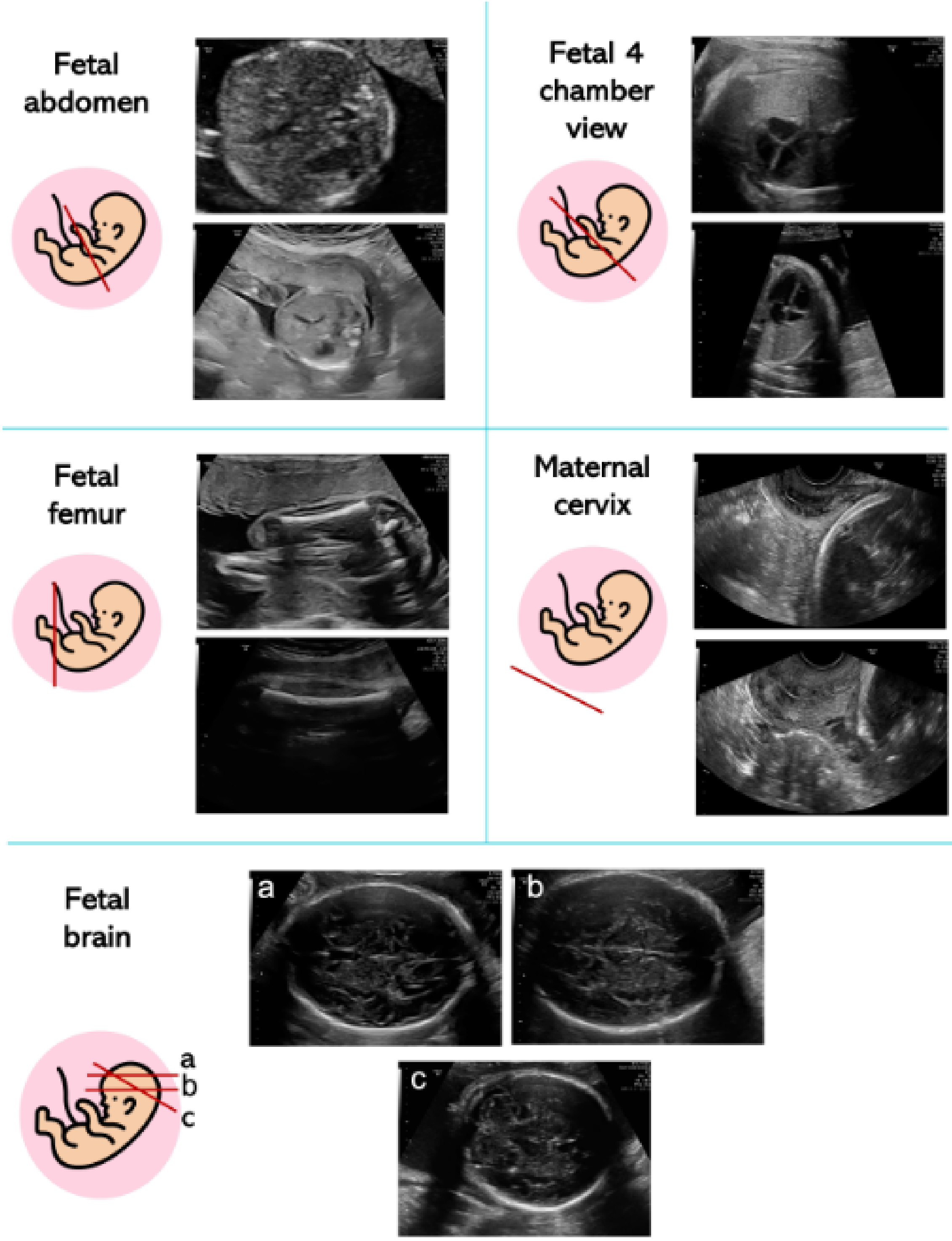

Figure 2.1: Introduced the process of Ultrasound imaging

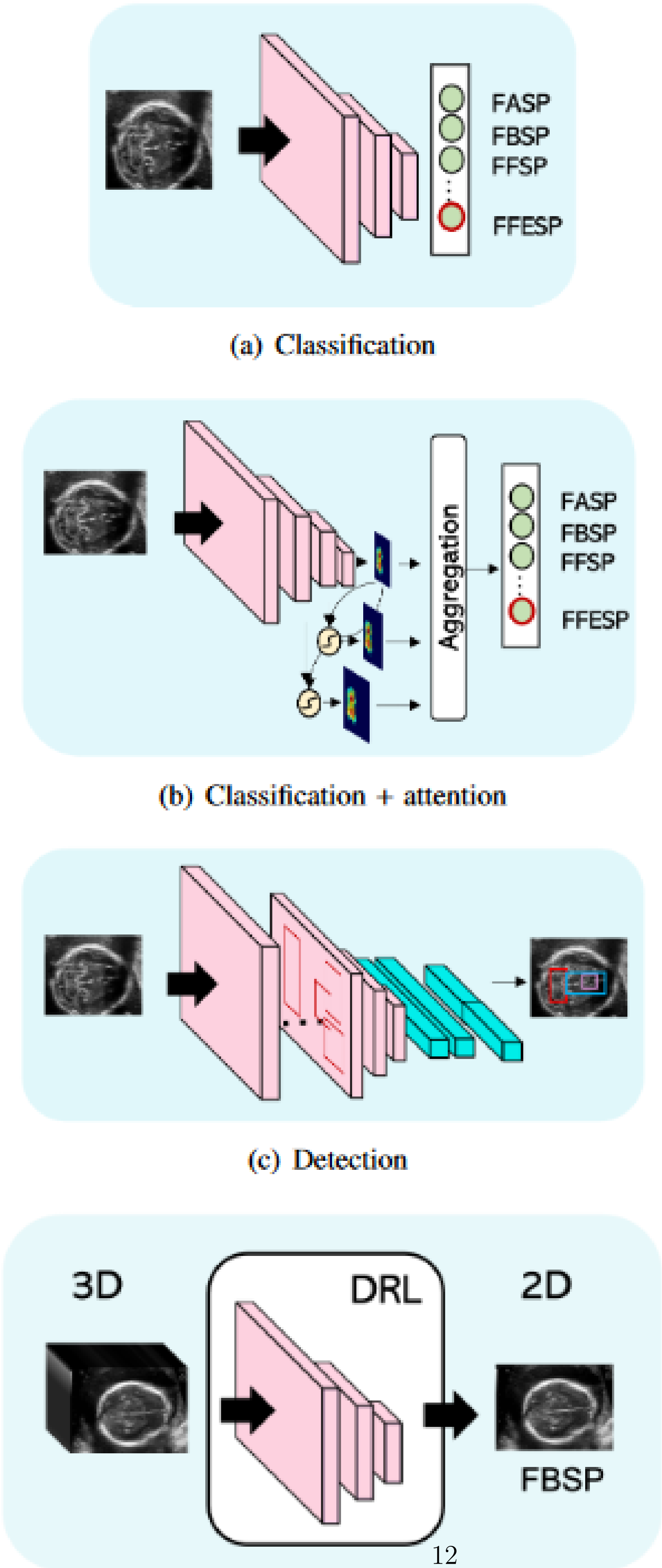

Figure 2.2: Performance Comparision

Chapter 3

METHODOLOGY

3.1 PROBLEM STATEMENT

The problem statement for ultrasound imaging of the fetus using deep learning involves addressing the challenges and limitations in accurately analyzing and interpreting ultrasound images to assess fetal health and development. Although ultrasound imaging is a widely used modality in obstetrics, it still requires expert interpretation and can be subject to variability and subjective assessment. Deep learning techniques have the potential to improve the accuracy, efficiency, and objectivity of fetal ultrasound analysis.[16]

One of the primary challenges is the complexity and variability of fetal anatomy and structures within ultrasound images. Different fetal structures, such as the brain, heart, limbs, and organs, need to be identified, segmented, and analyzed to assess their growth, position, and potential abnormalities. Deep learning models can be leveraged to automatically detect and segment these structures, reducing the reliance on manual annotations and subjective interpretations.

Another challenge is the presence of artifacts and noise in ultrasound images, which can degrade the quality and visibility of important anatomical details. Deep learning algorithms can be trained to effectively denoise ultrasound images and enhance the visibility of structures, enabling better analysis and diagnosis.[18] Additionally, fetal ultrasound images are often acquired in real-time, resulting in motion artifacts and limited spatial resolution. These factors can make it challenging to accurately measure and quantify specific fetal parameters. Deep learning approaches can aid in robustly tracking and estimating fetal measurements, such as head circumference, femur length, and abdominal circumference, enabling more accurate growth assessments.Moreover, the interpretation of fetal ultrasound images requires expertise and experience, which may not be readily available in all healthcare settings. Deep learning models have the potential to assist less experienced sonographers and clinicians by providing automated analysis, anomaly detection, and decision support, improving the accuracy and consistency of fetal assessments.

To address these challenges, deep learning algorithms need to be developed and trained on diverse and representative datasets to ensure their generalizability and effectiveness. The models should be able to handle the variability in fetal anatomy, adapt to different ultrasound machine settings, and provide real-time analysis for efficient clinical workflow.

By overcoming these challenges, ultrasound imaging of the fetus using deep learning can provide valuable insights into fetal health, aid in early detection of abnormalities, and support decision-making for appropriate prenatal interventions and care.[20]

3.2 PROBLEM SOLUTION

DATA PREPROCESSING

Data preprocessing plays a crucial role in ultrasound imaging when using deep learning techniques. It involves a series of steps that aim to enhance the quality of the ultrasound images, remove artifacts, and prepare the data for effective training and analysis. Proper data preprocessing is essential to ensure accurate and reliable results when applying deep learning algorithms to ultrasound imaging. One common preprocessing step is image normalization. Ultrasound images can exhibit variations in brightness, contrast, and overall intensity due to differences in acquisition settings or hardware. Normalization techniques are employed to standardize the intensity levels across images, making them more consistent. This step can involve rescaling pixel values, applying histogram equalization, or using other normalization methods to enhance image quality and reduce the impact of intensity variations.[19] Another important preprocessing step is image resizing or cropping. Deep learning models often require fixed-size inputs, so ultrasound images are often resized to a predefined resolution to ensure compatibility with the network architecture. Resizing can be done using interpolation methods such as bilinear or cubic interpolation to preserve important details while adjusting the image dimensions.

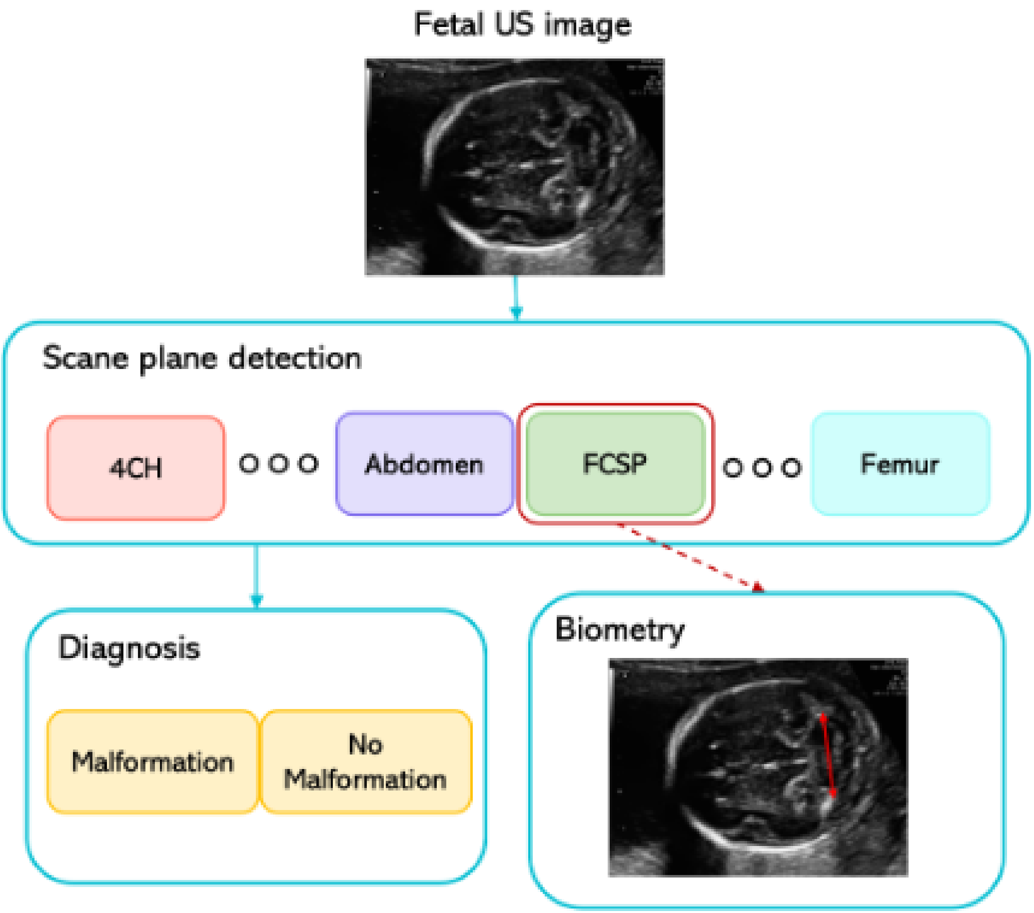

Figure 3.1: workflow of fetus ultrasound

Additionally, ultrasound images may contain noise, speckles, or artifacts that can affect the performance of deep learning models. Denoising techniques, such as filters or advanced algorithms like wavelet denoising, can be applied to reduce noise while preserving relevant image features. Artifact removal techniques, including speckle suppression filters or image inpainting, can also be employed to improve the quality and reliability of the ultrasound data.

Segmentation is a common task in ultrasound imaging, where specific structures or regions of interest need to be delineated. Preprocessing steps for segmentation often involve manual or automatic annotation of the regions to generate ground truth labels for training the deep learning model. Manual annotations can be performed by medical experts or through interactive tools. Automatic annotation methods, such as thresholding or edge detection algorithms, can also be utilized depending on the specific segmentation requirements.

Data augmentation is another important aspect of data preprocessing in deep learning. It involves generating additional training samples by applying various transformations to the original data. Augmentation techniques can include rotation, translation, scaling, flipping, or adding random noise to the images. Data augmentation helps increase the diversity and variability of the training data, improving the model's generalization and robustness.[22]

It is worth noting that data preprocessing steps may vary depending on the specific objectives, imaging modalities, and target applications in ultrasound imaging. The choice of preprocessing techniques should be guided by the nature of the data, the characteristics of the imaging system, and the requirements of the deep learning task at hand.

PROPOSED MODEL

The study's objective was to compare contemporary classification methods to the fresh dataset. This section will talk about the Multilayer CNN model that was provided in this study. The first portion of this paper describes the dataset,the second section discusses data preparation, and the third piece discusses the proposed model. The multilayer CNN model that we're going to suggest has three convolutional layers, three batch normalisation layers, three activation layers with ReLU activation function, two max-pooling layers, one fatten layer, one fully connected layer, and one activation layer with softmax activation function. In this model, a 256x256x3 picture serves as the data source to the network, while a 1x1x9 vector, representing the projected likelihoods of each class for the picture being used as the input across the nine classes, serves as the output. Table 1 provides a detailed design of the planned multilayer CNN.

Detail Explanation of CNN Model:

imageinput: A 256x256 image with three channels (for RGB colour pictures) serves as the network's input.

conv1 : This layer has 16 3x3 filters and a 1x1x16 bias vector. This layer produces a feature map with size of 256x256x16. [**?**]

batchnorm1 : This layer normalises the output of the layer before it, which can improve generalisation and help with training. It contains two parameters, offset and scale, each measuring 1x1x16 in size.

relu1 : This layer performs the Rectified Linear Unit activation function to the preceding layer's output element per element.

maxpooling1 : This layer reduces the spatial dimen- sions of the feature maps by a factor of 2, resulting in an output with dimensions of 128x128x16.

conv2 : This layer has 32 filters of size 3x3, and a bias vector of size 1x1x32. The output of this layer is a feature map with dimensions 128x128x32.

Batchnorm2 : This layer applies normalization to the output of the previous layer, which can help with training and improve generalization. It has an offset and scale parameter, each of size 1x1x32.

Relu2 : This layer applies the Rectified Linear Unit activation function element-wise to the output of the previous layer.

Maxpooling2 : This layer reduces the spatial dimen- sions of the feature maps by a factor of 2, resulting in an output with dimensions of 64x64x32.

Conv3 : This layer has 64 filters of size 3x3, and a bias vector of size 1x1x64. The output of this layer is a feature map with dimensions 64x64x64.

batchnorm3 : This layer applies normalization to the output of the previous layer, which can help with training and improve generalization. It has an offset and scale parameter, each of size 1x1x64.

Relu3 : This layer applies the Rectified Linear Unit activation function element-wise to the output of the previous layer.

FC : This layer takes the flattened output of the previous layer (a 1D vector of length 64x64x64=262144), and applies a matrix multiplication with weights of size 9x262144, followed by a bias vector of size 1x9. The output of this layer is a 1D vector of length 9, which represents the predicted class probabilities.

softmax : This layer applies the softmax function element-wise to the output of the previous layer, which nor- malizes the predicted class probabilities to sum up to 1.

classoutput : This layer outputs the final predicted class probabilities as a 1D vector of length 9.

The total number of parameters in the network is 2383113, which includes the weights and biases of all layers.

Table 3.1: Detailed architecture of the proposed Multilayer CNN model

S.No	Name	Activations	Learnables	Total learnables
1.	imageinput	256x256x3	-	0
2.	$conv_1$	256x256x16	Weights3x3x3x16, Bias 1x1x16	448
3.	$batchnorm_1$	256x256x16	Offset 1x1x16, Scale 1x1x16	32
4.	$relu_1$	128x128x16	-	0
5.	$maxpooling_1$	128x128x16	-	0
6.	$conv_2$	128x128x32	Weights 3x3x3x16x32, Bias 1x1x32	4640
7.	$batchnorm_2$	128x128x32	Offset 1x1x32, Scale 1x1x32	64
8.	$relu_2$	128x128x32	-	0
9.	$maxpooling_2$	128x128x32	-	0
10.	$conv_3$	64x64x64	Weights 3x3x3x16x32, Bias 1x1x32	18496
11.	$batchnorm_3$	64x64x64	Offset 1x1x64, Scale 1x1x64	128
12.	$relu_3$	64x64x64	-	0
13	fc	1x1x9	-	0
14	softmax	1x1x9	-	0
15	classoutput	1x1x9	-	0
-	Total	-	-	2383113

Chapter 4

DATA EVALUTION AND EXPERIMENTS

4.1 DATASET USED

The public can freely access the foetal ultrasound images and manual segmentations in the BioFACES (Bioimaging of Foetal and Children's Environmental Health Study) collection. It contains 266 images of the head, tummy, and limbs obtained between 14 and 40 weeks of pregnancy using a foetal ultrasound machine. The BioFACES project,which examines the relationship between exposure during pregnancy and the health outcomes of children, led to the development of the dataset. Using a Toshiba Aplio 500 ultrasound machine with a 2-8 MHz transducer, the ultrasound images were taken. Hand segmentations of foetal organs and structures, including the brain, spine, heart, liver, stomach, bladder, kidneys, femur,and humerus, are added to the photographs. The manual segmentations were carried out by experts and certified by a trained foetal sonographer.

The BioFACES Foetal Ultrasound Dataset may be used to analyse ultrasound images by segmenting foetal organs,identifying anomalies, and categorising them. Additionally, it may be used to develop and evaluate machine learning methods for analysing foetal ultrasound data.The dataset is available for research and may be accessed from the website of the Scientific Data journal. To ensure patient anonymity, it is crucial to stress that working with medical imaging datasets requires appropriate ethical approvals and respect to privacy norms.

4.2 PERFORMANCE METRICS

We use the average precision (AP), which is the average of P rec across all Rec values from 0 to 1, to measure the performance for localization tasks.

The F1-score (F1) measure is also widely used, especially for unbalanced datasets. These metrics can be computed for each patch, each image, or each patient. For segmentation tasks, we use the Dice similarity coefficient (DSC) and Intersection over Union (IOU) to evaluate the model performance (IoU). DSC is defined as follows and is equal to F1 :

$$DSC = \frac{2|XZ|}{|X| + |Z|} = \frac{2TP}{FP + FN + 2TP} = F1 \tag{4.1}$$

where X and Z represent the expected and labelled masks.

2) Accuracy: Accuracy is the measures to check the algorithm is correctly classifies data points.

$$Accuracy = \frac{NumberofCorrectPredictions}{TotalNumberofPredictions} \tag{4.2}$$

3) Precision: Precision is also the performance measure of how many predic- tions of the correctly class actually fall into that positive category.

$$Precision = \frac{NumberofCorrectlyPredictedPositiveInstances}{NumberofTotalPositivePositivePredictionsyoumade} \tag{4.3}$$

4) Recall: From the all positive examples in the data, recall is the another measures how many correctly class predictions have been made.

$$Recall = \frac{NumberofCorrectlyPredictedPositiveInstances}{NumberofTotalPositiveInstancesinaDataset} \tag{4.4}$$

Chapter 5

RESULTS AND CONCLUSION

5.1 EXPERIMENTAL EVALUATION

Performance comparison is a critical aspect when evaluating different models or algorithms in various domains, including computer vision, natural language processing, and machine learning. Comparing the performance of different approaches allows researchers and practitioners to assess their strengths, weaknesses, and suitability for specific tasks.

When conducting a performance comparison, it is essential to define appropriate evaluation metrics that align with the task's objectives and requirements. Commonly used metrics in performance evaluation include accuracy, precision, recall, F1 score, area under the receiver operating characteristic curve (AUC-ROC), mean average precision (mAP), and intersection over union (IoU), among others. These metrics provide quantitative measures to assess different aspects of model performance, such as classification accuracy, detection accuracy, segmentation accuracy, and overall model robustness.

Model	Accuracy	Precision	Recall	F1 Score
KNN	89.93	87	83.1	86
Xgboost	87.3	89	83.65	88
Decision Tree	88	83.3	81.5	82
Proposed Model	92.1	89	86	89.34

[a]

[a] all values are in percentage

Figure 5.1: Performance Comparision

To perform a fair and unbiased performance comparison, researchers typically use standardized datasets and evaluation protocols. Standard datasets ensure that the models are evaluated on the same set of samples, allowing for direct comparisons. Additionally, cross-validation or train-test splits are often employed to account for variations in performance due to data distribution and to ensure generalization capabilities. In performance comparisons, researchers may use baseline models or existing state-of-the-art approaches as reference points. Baseline models provide a benchmark to evaluate the performance improvements achieved by new algorithms or techniques. State-of-the-art models, on the other hand, represent the current best-performing methods in a particular domain and serve as a point of reference for assessing the competitiveness of new approaches.

Performance comparison studies often include statistical analyses to determine the significance of performance differences between models.Techniques such as t-tests, ANOVA, or non-parametric tests can be used to assess the statistical significance of performance variations.

It is crucial to properly report the results of performance comparisons, including quantitative metrics, statistical significance tests, and visualizations such as graphs or tables. Care should be taken to present the results accurately, objectively, and transparently to facilitate reproducibility and allow readers to draw meaningful conclusions.

5.2 CONCLUSION

In conclusion, it has been shown that mathematical models are the first to be sufficiently developed for widespread application to actual matronly-fetal clinical circumstances, notably as assistance for overall US identification. Trans- ferability and application categorization, which is necessary for contemporary clinical diagnosis, still has considerable problems. We hope that our analysis and the maternal-fetal US dataset will serve as a springboard for further investigation. Recognising that many more methods could have been benchmarked and that computational models may have benefitted from earlier processes like picture segmentation rather than assessing images in their whole (particularly in the case of highly fine brain plane identification), we acknowledge that many more techniques could have been tested. [16] However, improving performance was not the study's main purpose; rather, by making the dataset available to the public, we hope to promote more of this kind of investigation.

Ultrasound imaging of the fetus using deep learning is a promising field that has many clinical applications and challenges. Deep learning can improve the quality and accuracy of ultrasound images and enable automatic tasks such as segmentation, classification, and localization of fetal structures and abnormalities. Deep learning can also facilitate the measurement of fetal biometry and the detection and diagnosis of fetal malformations. However, there are still limitations and difficulties in dealing with noisy and blurry images, inter- and intra-observer variability, multi-center datasets, and fine-grained plane categorization. Further research and development are needed to overcome these challenges and to validate the performance and reliability of deep learning models in real clinical settings.

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