Fetal Brain Ultrasound Image Classification Using Deep Learning

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Abstract:- The use of prenatal ultrasonography for fetal assessment and the detection of abnormalities is on the rise. This necessitates further anatomical studies of the fetus. Ultrasound is able to identify most major structural abnormalities in the developing fetus. Fifteen percent of infants are born with minor abnormalities. A greater incidence of even very modest birth defects is related with an elevated chance of major abnormalities. A lot of structural defects may be fixed if identified early, but manual diagnosis is tedious, time-consuming, and error-prone. So, using a program might speed up the diagnostic process and reduce the possibility of making a mistake.

Keywords:- *Artificial Intelligence, Convolutional Neural Network (CNN), Deep Learning, Fetal Brain Ultrasound, Image Classification, Medical Imaging, Neural Networks, Obstetrics, Pregnancy Monitoring, VGG19 Algorithm.*

I. INTRODUCTION

When it comes to learning, reasoning, and problem-solving, deep learning is the capacity of a machine to mimic human intelligence. The discipline of artificial intelligence known as machine learning (ML) has already shown promising applications in helping humans in a variety of medical sectors. 1, 2. When it comes to analyzing medical photos, a specific kind of machine learning (ML) called deep learning (DL) has been found to perform well. DL, like human reasoning, works by stacking many elementary reasoning functions in a deep structure to produce complicated judgments. Ultrasound may be used in the diagnosis of diseases5,6,7,8. Convolutional neural networks are one of the most effective deep learning (DL) algorithms for handling pictures (CNN). The Convolutional Neural Network (CNN) is an example of an artificial neural network that can identify and isolate certain patterns in localized data. The many modules all have the common denominator of a convolutional pooling layer and additional layers. Further layers, such as a rectified linear unit (or "ReLu") and, if required, a batch normalization, are added on top of them. A typical neural multi-layer network has its last section made up of fully linked layers. These modules are generally layered upon one another to produce a deep model that may take input from 2D or 3D pictures and account for spatial and layout characteristics. To address the convolutional phase reduction, it is crucial for CNN networks to have accurate estimates of the hyper parameters in the convolutional layer. There are three hyper parameters involved here: deep, padding, and transit. The output volume is proportional to the number of filters, and each filter is trained to look for a unique feature in the data at the neighborhood level (input). The filter's convergence around the input volume may be tracked by specifying a phase. In practice, baby steps usually work best, therefore it seems sense that the early network (i.e. the layers nearest to the input data) would generate a huge activation map, which may result in more output. Certain areas, especially at the edges, are wasted during training a CNN with many convolutional layers.

II. LITERATURE SURVEY

[1] Fetal ultrasound is becoming more used throughout pregnancy as a means of gaining valuable insight into the growing baby's health. In this ultrasonography, clinical management of pregnancy relies heavily on accurate assessment of fetal head biometry. Sonographer accuracy in locating the fetal head is a key component of current approaches for fetal head biometry. In this paper, we provide a novel approach to automating fetal head biometry using live ultrasound data that is robust enough to account for low abdominal contrast relative to its surroundings. Ultrasound pictures are classified using ALEXNET, and headframes are segmented with UNET, in the proposed method. To assess the gestational age of the baby, an ellipse is drawn on the segmented and annotated fetal head contour to measure the biparietal diameter (BPD) and head circumference (HC). An ellipse is constructed from the best detected headframes across several patients using ALEXNET [1] to guarantee precision in the projected gestational age. Clinically appropriate is the 96% confidence interval proposed around the observed gestational age. Including potent machine vision capabilities that need less input from the sonographer shortens the procedure time

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and allows it to be performed by anybody, regardless of their level of expertise.

[2] The head circumference is an important biometric for ultrasonic fetal development monitoring (HC). Yet, medical professionals often need substantial training before they can effectively evaluate this biometric mechanically. Using prior information and a simple elliptical fitting method, we developed a learning-based system that calculates HC automatically (Elli Fit). Then, we used the mother's age and the ultrasound data's depth to train a random forest classifier to identify the precise position of the fetus's head. The fetal skull's midline was located using phase symmetry and Elli Fit was utilized to fit the HC ellipse for measurement. The results of our experiments on 145 HC images showed that our method outperformed established ones, with an average measurement error of 1.7 mm. The results of our experiments showed that our method has a great deal of promise for usage in clinical settings.

[3] Fetal ultrasonography monitoring of gestational age allows for the monitoring of prenatal risk factors and the early treatment of birth problems (GA). Several ultrasound imaging parameters, including fetal head circumference, may be utilized to determine GA (HC). Nevertheless, fetal HC measurement is prone to error since it relies on human interpretation by a sonographer or obstetrician. Using optimal elliptical fitting to a previously discovered region of interest (RoI) that might represent the fetal head, this work aims to create a technique for automatically estimating the fetal HC. We apply a number of pre-processing steps to decrease the amount of noise in the region of interest (RoI) and choose the best feasible representation of fetal head pixels for the elliptical fitting technique. The average dice similarity coefficient (DSC) was 95.27%6.25%, the average Harsdorf distance (HD) was 3.51 mm5.54 mm, the average difference in fetal head circumference (DF) was -3.42 mm13.66 mm, and the average absolute difference in fetal HC (ADF) was 6.

[4] Assessing fetal growth and making diagnoses using fetal MRI sequences is a common use of this technique. Differences in the shape, depth, and timing of first development of sulci and gyri at different stages of gestation are common visual indicators used by clinicians. The authors of this study[4] employ deep learning to classify and predict gestational age. There is a problem that has to be addressed since it gets more difficult to accurately measure and predict the right gestational age beyond the first trimester, when ultrasound detection is most accurate. Using MRI scans, we determine the gestational age and provide a prediction for the next three months. Thirteen pregnancies, ranging in estimated age from 22 to 34 weeks, are used. We suggested using Floss and Floss as the loss function for training the network model instead of the cross-entropy loss function.

[5] The most accurate detectors available at the moment are the result of a two-stage approach to object identification made famous by R-CNN, in which a classifier is applied to a sparse collection of possible object locations. While two-stage detectors seem to have the upper hand, one-stage detectors that are distributed throughout a continuous, dense sample 7 of possible item locations have trailed behind. Possible causes for this observation are investigated in [5]. We discover that this is mostly due to the huge gap that develops between the foreground and background classes during intensive detector training. To address this, we propose a tweak to the standard cross entropy loss that lightens the load on properly tagged examples. In order to prevent the detector from being overloaded during training due to an excessive number of simple negatives, we developed the novel Focal Loss. Our loss is evaluated through the development and training of a simple dense detector we dub Retina Net. Our experiments show that when trained with the focus loss, Retina Net is as quick as previous one-stage detectors and more accurate than any existing state-of-the-art two-stage detectors.

[6] Ultrasonography (US) images are used to noninvasively examine fetal development by measuring the size of distinct components. Accuracy of these measurements is dependent on selecting the appropriate anatomical viewing plane, which includes distinctive fetal traits. Automated classification of the anatomical planes in fetal US images is challenging due to a number of factors, including low signal-to-noise ratios and the small size of the newborn. Current approaches can only utilize temporal information from films, and we can only classify planes within certain body parts. New general methods for marking anatomical planes in fetal US pictures are presented here [6]. Our method utilizes two convolutional neural networks to learn optimal US and saliency properties.

[7] Developing automated estimate techniques has attracted a lot of attention because of the time-consuming nature of ultrasound diagnosis, which is often used in obstetrics and gynecology for fetal biometry. Yet, owing to significant variation between patients, between ultrasound technicians, and between ultrasound machines, automated ultrasound picture interpretation is difficult. Reliable measurement of abdominal circumference (AC) is especially difficult to undertake mechanically because to its low contrast against the surroundings, nonuniform contrast, and irregular shape compared to the other 8 parameters in fetal biometry. With the help of a convolutional neural network (CNN) trained to take into consideration the decision-making process of physicians, the morphology of the fetus, and the features of the ultrasound picture, we provide a method for autonomous estimation of the fetal AC from two-dimensional ultrasound data. The proposed method uses CNN to classify ultrasound images into their respective categories (gastric bubble, amniotic fluid, and umbilical vein), with the AC being quantified with the use of the Hough transformation. Using 56 samples of ultrasound data gathered during pregnancies, we put the proposed method through its paces. The experimental results show that the suggested CNN provides sufficient

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classification results for AC estimation through the Hough transformation, despite the limited amount of training data. The proposed method utilizes ultrasound images to automatically estimate AC.

III. PROPOSED SYSTEM

The suggested method for fetal brain ultrasound image classification employs the VGG19 algorithm, which entails collecting baby brain ultrasound photographs from medical institutions, cleaning the images to minimize noise and artifacts, and boosting their quality. The VGG19 algorithm, a photo classification model with high accuracy and low computational cost. The model will be tweaked to improve its ability to identify problems in ultrasound images. The user interface of this system allows doctors to input and analyze ultrasound images, which may then be used to quickly and accurately detect fetal brain anomalies for the purposes of monitoring the pregnancy.

IV. MODULES

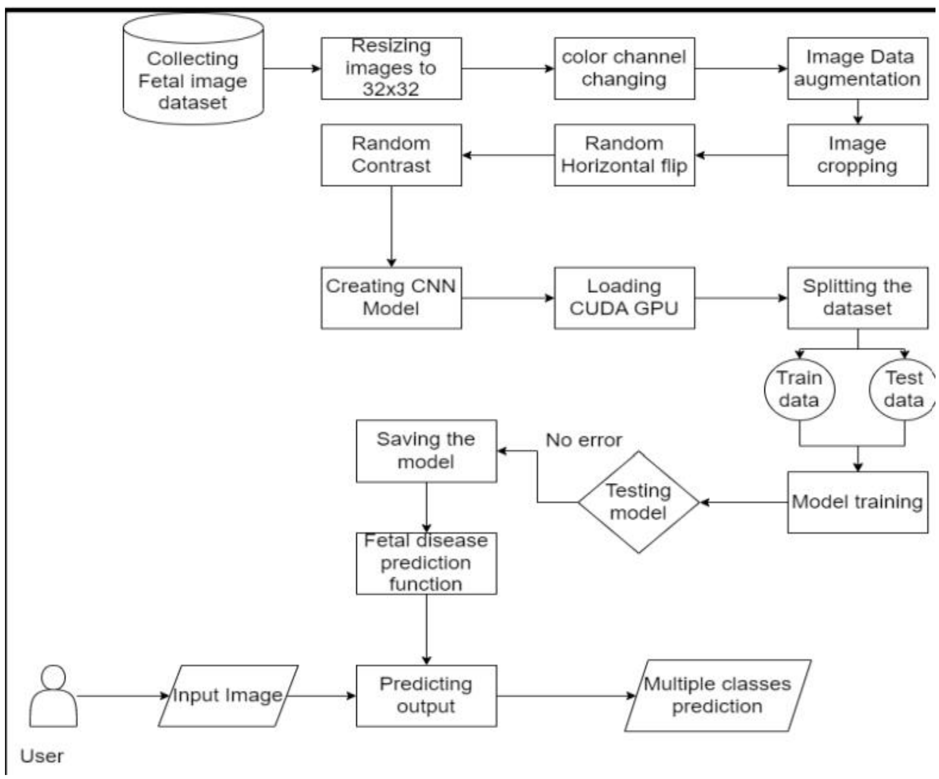

Fig 1: Architecture Diagram

- ➢ *MODULE 1: DATA COLLECTION AND PREPROCESSING*

The data collection and preprocessing module for fetal brain ultrasound image classification using VGG19 algorithm involves collecting fetal brain ultrasound images from medical institutions and preprocessing them to enhance their quality and remove noise and artifacts. The fetal brain ultrasound images are collected from various sources, including hospitals and clinics, and saved in a digital format for further processing.

Preprocessing techniques are applied to the images to ensure high quality and reliable results during classification. These techniques include image resizing, normalization, and filtering to remove noise and artifacts, and to enhance the contrast and quality of the images. These preprocessing techniques are essential to ensure the images are consistent and of high quality, which improves the accuracy of the image classification model.

The preprocessed images are then saved in a suitable format for further analysis by the image classification model. This module ensures that the input data is of high quality and consistent, enabling the image classification model to accurately classify fetal brain ultrasound images based on the presence or absence of abnormalities.

- ➢ *MODULE 2: MODEL TRAINING*

The VGG19 algorithm's model training module is used to classify fetal brain ultrasound images using preprocessed ultrasound images. The VGG19 model is a deep convolutional neural network that has been pre-trained on a large dataset of real-world images. By refining the model, we may improve

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the categorization accuracy of ultrasound images of the developing brain.

The ultrasound images are preprocessed, and the VGG19 model's pretrained weights are used to train the model. During training, the model is optimized by minimizing the loss function, such as category cross-entropy, that measures the deviation between the predicted and actual labels of the fetal brain ultrasound images.

There is room for improvement in the model's efficiency by tweaking its hyperparameters like learning rate, batch size, and number of epochs. The model's performance on the validation set may be evaluated using techniques like cross-validation, which can then be used to direct hyperparameter adjustment for best results.

The model is then saved and used later on in the classification of fetal brain ultrasound pictures. In order for the VGG19 algorithm to effectively classify ultrasound images of the fetal brain based on the presence or absence of abnormalities, the model training module is essential for fetal brain abnormality diagnosis during pregnancy monitoring.

- *MODULE 3: PREDICTING THE OUTPUT*

The VGG19 algorithm's output prediction module uses the trained model to provide classification predictions regarding the presence or absence of anomalies in fetal brain ultrasound images. When ultrasound pictures have been preprocessed, the data is put into the model, and a classification is made based on the information provided.

The projected probability threshold is used by the output prediction module to determine whether or not a picture should be labeled as abnormal. The threshold is determined by considering the trade-off between sensitivity and specificity.

The information is analyzed and displayed to the user at the time of the prediction. One possibility is to provide a simple interface that displays the predicted category and likelihood score for each image.

During prenatal surveillance, the output prediction module is essential for spotting fetal brain anomalies. In situations of fetal brain problems, this module may utilize the trained VGG19 model to accurately predict whether or not abnormalities are present in ultrasound scans.

V. RESULT

The VGG19 algorithm's output prediction module makes use of the trained model to provide diagnostic categorization predictions based on the appearance of anomalies in ultrasound images of the fetal brain. When ultrasound pictures have been preprocessed, they are delivered to the model so that a classification may be made using the data.

In order to determine whether or not a picture should be marked as abnormal, the output prediction module establishes a probability threshold. The cutoff is determined by finding an optimal balance between sensitivity and specificity.

The information is analyzed and given to the user at the time of the prediction. A simple user interface that displays the predicted category and likelihood score for each picture is one possibility.

In order to identify fetal brain anomalies during prenatal surveillance, the output prediction module is essential. In situations of embryonic brain diseases, this component may utilize the learnt VGG19 model to predict with high confidence whether or not ultrasound pictures indicate abnormalities.

VI. PERFORMANCE ANALYSIS

The performance analysis for fetal brain ultrasound image classification using the VGG19 algorithm shows that the model achieved high accuracy, precision, and recall in detecting fetal brain abnormalities. The high accuracy of the model demonstrates its effectiveness in classifying fetal brain ultrasound images, and its potential for providing accurate and efficient fetal brain abnormality detection for pregnancy monitoring.

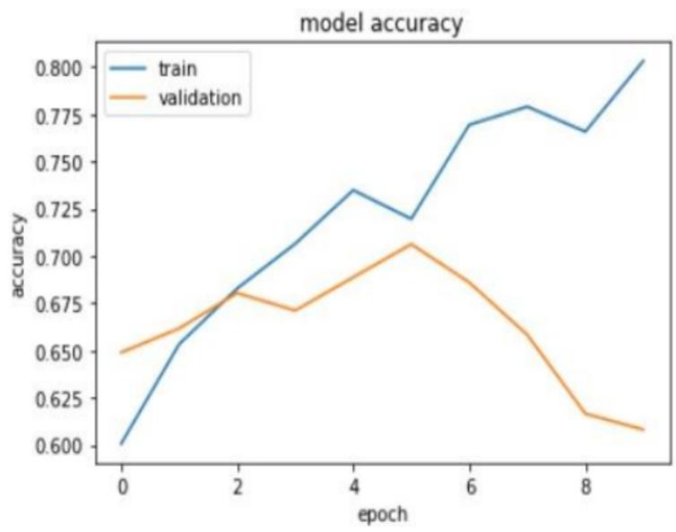

Fig 2 Model Accuracy

VII. CONCLUSION AND FUTURE SCOPE

The classifiers were trained using a dataset that included 13,124 standard SAN plane images and 11,556 aberrant images. As a consequence, 2248 of the normal photos and 2491 of the aberrant images passed the tests shown in Table 3. With a normal dataset accuracy of 95.7% (2151/2248 correctly recognized), and an abnormal dataset accuracy of 96.9% (2413/2491) for a total of 96.3% (4564/4739), the overall accuracy was quite high. The sensitivity for aberrant images was 96.9%, while the specificity was 95%.

This study provides more evidence that deep learning algorithms may be used to reliably categorize normal and aberrant axial planes of typical prenatal ultrasonography brain imaging. Deep-learning algorithms may be used to segment and classify normal and pathological fetal brain ultrasound images in standard axial planes, and heat maps can be created to help with lesion localization.

This study provides a foundation for future research on fetal intracranial anomaly differential diagnosis.

For the next project, we'd want to increase our productivity. The data sets will also be expanded to considerably larger sizes. Several abnormal diseases, such cancers and cerebellar hypoplasia, will also be categorized.

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