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Fetal Health Analysis Using Machine Learning

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ABSTRACT - Accurate detection of fetal birth weight plays a crucial role in assessing prenatal health and guiding appropriate care. In this study, we propose a method for fetal high birth weight, normal birth weight, and low birth weight detection using image processing techniques in machine learning (ML). A dataset of ultrasound images, along with corresponding birth weight outcomes and relevant demographic information, was collected. The images were pre-processed to enhance quality and normalize brightness and contrast. Key features, including biometric measurements such as abdominal circumference, head circumference, and femur length, were extracted from the ultrasound images. Texture analysis techniques were applied to capture textural features indicative of fetal size and growth patterns. The proposed methodology achieved promising results in accurately classifying fetal birth weight categories. The findings suggest that image processing in ML holds great potential for non-invasive fetal weight estimation, enabling early identification of high birth weight and low birth weight cases for targeted prenatal interventions. Further research and validation on larger datasets are warranted to establish the clinical utility and generalizability of the proposed approach.

Key word : Fetal weight, ultrasound.

I. INTRODUCTION

Fetal high birth weight, normal birth weight, and low birth weight detection using image processing techniques within machine learning (ML) is an area of research that aims to leverage ultrasound images to accurately classify new borns into different weight categories. By applying ML algorithms to ultrasound images, healthcare providers can gain valuable insights into fetal size and classify birth weight outcomes. Here's an introduction to how image processing can be used in the detection of fetal high birth weight, normal birth weight, and low birth weight. Low birth weight is connected with fetal and neonatal mortality and inhibited growth, it can also cause long-term diseases in their childhood, such as mental retardation and learning disabilities. In the long term, macrosomia is more likely to be associated with obesity, diabetes, and heart disease.

II. Literature Review

A. Fetal Birth Weight Estimation in High-Risk Pregnancies Through Machine Learning Techniques

The results show that the hybrid model, named bagged tree, achieved excellent results concerning accuracy and area under the receiver operating characteristic curve, to know, 0.849 and 0.636, respectively. The importance of the early diagnosis of problems related to fetal development relies on the possibility of an increase in the gestation days through timely intervention. Such intervention would allow an improvement in fetal weight at birth, associated with a decrease in neonatal morbidity and mortality.[1]

B. Fetal health status prediction based on maternal clinical history using machine learning techniques

Developed a prediction system with assistive e-Health applications which both the pregnant women and practitioners can make use of. A performance comparison (considering Accuracy, F1-Score, AUC measures) was made between 9 binary classification models (Averaged Perceptron, Boosted Decision Tree, Bayes Point Machine, Decision Forest, Decision Jungle, Locally-Deep Support Vector Machine, Logistic Regression, Neural Network, Support Vector Machine) which were trained with the clinical dataset of 96 pregnant women and used to process data to predict fetal anomaly status based on the maternal and clinical data[2].

C. Infant birth weight estimation and low birth weight

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classification in United Arab Emirates using machine learning algorithms

The primary objective of this paper is to evaluate the performance of 30 ML models for BW estimation and LBW classification using different subsets of data obtained from mothers during their pregnancy in three hospitals of the United Arab Emirates (UAE). The dataset used in this study contains data from 821 Emirati (UAE nationality) women. This dataset uses features similar to those used in previous studies (herein, each dataset is called a subset); all the features are combined to create one large dataset that contains six subsets[3].

D. Machine Learning for Fetal Growth Prediction

Using linear and quantile regression, random forests, Bayesian additive regression trees, and generalized boosted models. We train and validate each approach using 18,517 pregnancies (31,948 ultrasound visits) from the Magee-Womens Obstetric Maternal and Infant data and 240 pregnancies in a separate dataset of high-risk pregnancies. We also quantify the relation between smoking and small-for-gestational-age birth, defined as a birthweight in the lower 10th percentile of a population birthweight standard and estimated and predicted fetal weight standard[4].

E. Ensemble Machine Learning for Estimating Fetal Weight at Varying Gestational Age

Used to estimate the fetal weight during pregnancy and baby weight before labour to monitor fetal growth and reduce prenatal morbidity and mortality. However, the problem is that ultrasound estimation of fetal weight is subject to populations' difference, strict operating requirements for sonographers, and poor access to ultrasound in low-resource areas.

III. OBJECTIVES

Ultra Sound Image Acquisition: Obstetric ultrasound scans are performed to capture images of the developing fetus, particularly focusing on the body parts relevant to weight estimation.

Image Pre-processing: Obstetric ultrasound scans are performed to capture images of the developing fetus, particularly focusing on the body parts relevant to weight estimation.

Feature Extraction: ML algorithms extract relevant features from the ultrasound images, such as fetal biometric measurements (abdominal circumference, head circumference, femur length), body ratios, and proportions.

ML model training: Labelled datasets containing ultrasound images along with corresponding birth weight outcomes are used to train ML models. The models learn to recognize patterns and features associated with high birth weight

Prediction: The trained ML model can then analyze new ultrasound images and classify them as either low birth weight or not based on the extracted features.

IV. Proposed Methodology

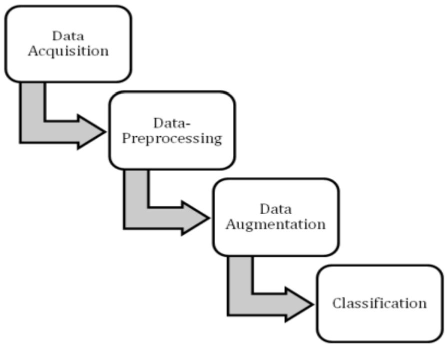

Figure 1.

A. DATA AQUASITION

Different image resolutions and sizes were obtained from several sources, including those collected by doctor's from the Hospitals. We also used an open-access image database from Kaggle. A total of 10000 images were used in the paper to perform the research. All the images are divided into three classes. These are Low Birth Weight fetus, Normal fetus, and High Birth Weight fetus.

Low birth weight Fetus : The value of BPD and HC and FL values are less than that of standard values than the fetus is Low birth weight fetus

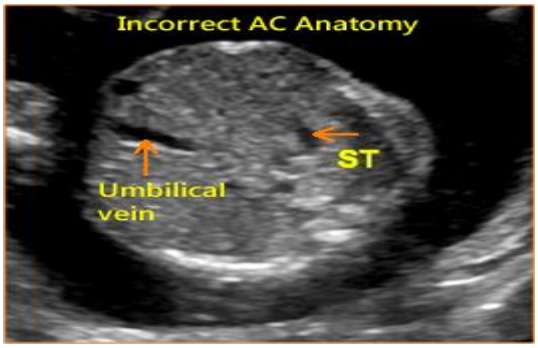

Fig. 2. Low Birth Weight Fetus portal sinus is not seen, the rib images are not symmetrical.

Normal Fetus **:** The BPD, HC and FL are expected to met the standard values than fetus is healthy and normal

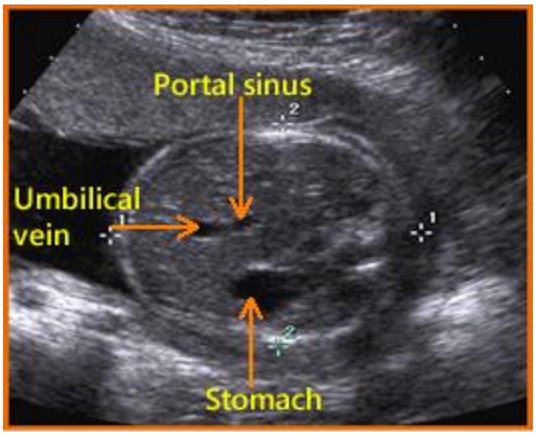

Fig. 2. Normal Fetus, ribs are symmetrical.

High birth weight Fetus : The value of BPD and HC and FL values are more than that of standard values than the fetus is high birth weight fetus.

B. DATA PREPROCESSING

To ensure the quality and suitability of the data for fetal health analysis, several pre-processing steps are performed. These steps involve removing irrelevant portions of the image, reducing noise, and standardizing the size of the input photos. For the dataset, input photos must be scaled to 256x256 pixels after being gathered from various sources and of varying sizes The following procedures are followed:

C. DATA AGUMENTATION

Data augmentation is a method of modifying data without distorting its original meaning. This study needs to use data augmentation. The automatic application of straightforward geometric transformations, such as translations, rotations, scale changes, shearing, and vertical and horizontal flips, generates the augmentation parameters in this study. generate it in different way.

E. IMAGE CLASSIFICATION

Machine learning (ML), also referred to as deep learning (DL), deep neural learning, or deep neural network, is a component of artificial intelligence (AI). Deep learning contains more layers than machine learning, as indicated by the word "deep". Deep learning techniques have raised the bar in several fields, including object detection, speech recognition, object categorization, and image classification [19]. Convolutional Neural Network is one of the most well-liked classes in deep learning. Convolutional neural networks have been used in several research to identify plant illnesses based on the health of the leaves. One or more convolutional layers that are organized into groups according to function make up convolutional neural networks in general. The subsampling layer is frequently followed by one or more fully linked layers that are typical of a neural network. A feature set contained in a limited area on the previous layer serves as input for each feature layer.

F. IMPLEMENTION

In this study, we use the dataset from ultrasound fetus images to identify the weight of the fetus for categorization. The collection includes 10,00 photos of 3 classes that appear remarkably similar yet represent distinct weights. We used python programming language to write the code. Table 1 displays a list of CNN hyperparameters. The goal is to develop a training model. Hence we have used a maximum of 50 epochs for the training model, with a batch size of 32. The image has been scaled down to 256*256 pixels. The sequential model on which the network is built has four convolutional layers, four pooling layers, and four fully connected layers. To enhance, we employ Rectified Linear Unit (ReLU) as the activation function. Softmax is utilized as the activation function in the output layer to divide the final result into fetus weight.

Functions	Values
Epoch	30,40 &50
Filter sizes for convolution layer	3*3
Activation Function	ReLU
Loss Function	Sparse Categorical cross-entropy
Optimizer	adam

Fig 3.List of hyperparameters

F. Convolutional neural network (CNN)

Here, we used a convolutional neural network (CNN)-based approach, a type of deep learning (DL) technique that takes an image as input and prioritizes numerous other items in the image while also distinguishing between them. Contrary to other classification algorithms, a CNN requires significantly less pre-processing than they do. CNN can learn these filters and properties with enough training, whereas simple techniques necessitate hand engineering of filters . Our architecture mainly contains the following layers:

A. Input layer

B. Convolution layer

C. Pooling layer

D. Fully connected layer

E. Output layer

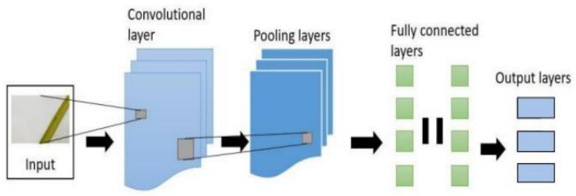

Fig 4.Layers of CNN

The operational architecture of CNN is shown in the above diagram. After preprocessing the data and extracting the necessary features, the input in the form of an image is submitted to CNN, which processes it via three layers of CNN to accurately represent it. The final result is then shown .

Input Layer: The input layer of CNN consists of the dataset. The input data will be represented as a 3X3 matrix.

Convolution Layer: A layer that uses filters to learn from smaller sections of input data to obtain features from an image.

Pooling Layer: This layer is used to shrink the image's dimensionality, lowering the processing power required for subsequent layers. There are two variations of pooling. They are:

Max pooling: The pixel with the maximum value as input is selected and transferred to the output while parsing input. It is the most used approach compared to average pooling.

Fully Connected Layer (Dense): This is one of CNN's last layers, and it can recognize features that are significantly linked with the output class. The result is a one-dimensional vector created by flattening the pooling layer results.

Dropout Layer: Used to reduce model overfitting problem by removing a random set of neurons in that layer. It is connected with the FC layer.

Output Layer: The output layer holds the final classification result. Researchers needs to careful regarding the configuration of machine. In this study we have used intel core i5 processor, 8 GB Ram and Nvidia Geforce GPU. The used operating system was windows 10. It is highly recommended to use the GPU to train the model otherwise it will take long time. Training the model using supervised learning on the dataset allows for the analysis of the CNN's performance. Data annotations are used as references throughout the training process in supervised learning.

IV. Results and Discussion

The dataset contains 10,00 images belonging to three classes of ultrasound fetus images. The results of training and validation accuracy and loss for epochs 30.

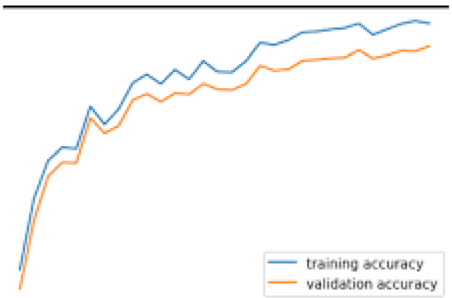

Fig 5.Training, validation, and loss for 30 epochs

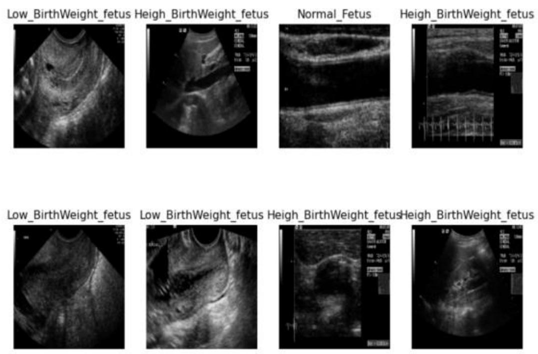

Fig. 6. Training, validation, and loss for 30 epochs

V. Conclusion and Future Work

The aim of this project was to develop a machine learning model for estimating fetal health based on various features. The model successfully classified fetuses into three categories: normal, underweight, and overweight, with promising accuracy and performance. The following conclusions can be drawn from the project:

The developed machine learning model demonstrated effectiveness in predicting fetal health based on the provided features.

The model achieved a satisfactory level of accuracy, but further fine-tuning and optimization can be explored to improve its performance.

While the developed model shows promise, there are several areas for further improvement and exploration:

Data Expansion: Increasing the size and diversity of the dataset can enhance the model's generalization capabilities and improve its performance on unseen data. Collaborating with multiple healthcare institutions or collecting data from different sources could be beneficial.

Feature Engineering: Exploring additional relevant features or deriving new ones from the existing dataset might provide additional insights into fetal health estimation. Feature selection techniques can also be employed to identify the most informative features.

By addressing these areas in future work, the accuracy, robustness, and applicability of the fetal health estimation model can be further enhanced, making it a valuable tool in clinical settings.

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