INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE

ISSN: 2057-5688

FETAL ANOMALY DETECTION USING DEEP LEARNING

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Abstract: The structural defects in a fetus that can lead to a complicated pregnancy, and disabilities later in life are known as Fetal anomalies. The key to the prevention of these later disabilities include early detection and intervention. These anomalies in the fetus are traditionally detected by specialists by physically analysing the medical images which actually leads to serval limitations like the the cost of training a qualified radiologist and the general limitations of human beings such fatigue, lack of speed and experience may lead to delayed or erroneous diagnosis, hence delaying intervention. This research processes the use of Deep learning framework in the detection of fetal anomalies from ultrasound scans. Thisfocuses on the detection of fetal anomaly, Congenital Talipes Equinovarus (CTEV) which is one of the most common musculoskeletal defects that can be corrected by early detection and intervention. The objective of this study is to develop a deep learning model that can analyze ultrasound scans and detect Congenital Talipes Equinovarus. Anomaly detection is a growing research area in machine learning literature, where the goal is to distinguish between normal samples
anomalous samples in a dataset.

I. INTRODUCTION

Fetal anomalies refer to unusual or unexpected conditions in a baby's development during pregnancy. Fetal anomalies may also be known as congenital anomalies or birth defects.These defects can complicate pregnancy and cause negative consequences to the developinginfant. Other terms used in referring to fetal anomalies include congenital anomalies, congenital malformations, congenital disorders, and congenital abnormalities. The purpose of this project is by using the Deep Learning frameworks in thedetection of Congenital talipes equinovarus (CTEV). A deep learning framework known as “Anomalib” is used here for the detection of Congenital talipes equinovarus (CTEV). Congenital talipes equinovarus, is alsoknown as clubfoot. Club foot is a birth defect that affects the foot, and the foot appears to bebent out of shape. This is a type of musculoskeletal defect. This project proposes the use of Deep Learning framework, Anomalib for unsupervised image anomaly detection. Traditional computer vision algorithms are not effective as the difference between normal samples and abnormal samples can be very small. So, Deep Learning based approaches can automatically learn the difference between normal and abnormal features. An Ultrasound scan, also known as a sonogram, is a medical test that employs the usageof high frequency sound waves to visualize the internal parts of the body. Additionally, ultrasound can share the most preferred imaging and monitoring techniques all over the world during the pregnancy period because unlike the other medical imaging techniques, ultrasound does not use radiation. Congenital Talipes Equinovarus is a congenital anomaly that affects the foot. If ignored or left untreated, congenital talipes equinovarus scares train movement by making walking hard, painful, or even impossible. However, early detection and treatment are assumed to be the key topreventing latedisabilities. Although radiologists can interpret ultrasounds and detect anomalies early, it takes several yearsand a huge financial cost to train a competent radiologist.

ISSN: 2057-5688

II.REVIEW OF LITERATURE

Cardiotocography (CTG) is a monitoring approach applied extensively all over the world to check and determine the distress level of the fetus. CTG entails two major signals: fetal uterine contraction (UC) and heart rate (FHR).

[CITATION Fai21 \l 1033] checked the behaviors and performances of neural network training algorithms comparisons on classification tasks of the CTG traces. In their study, the neural networks were categorized into five groups: Resilient Backpropagation, Gradient Descent, Quasi-Newton, Conjugate Gradient, and Levenberg-Marquardt. Although all the five algorithms provided impressive results, the algorithms that performed the best classifications were obtained with Resilient Backpropagation (RP) and Levenberg-Marquardt backpropagation (LM) algorithms. The outputs of Resilient Backpropagation and Levenberg-Marquardt backpropagation were 89.69% and 86.14%, respectively. Therefore, the study confirmed ANN as a useful machine learning tool to classify fetal heart rate recordings [CITATION ERa20 \l 1033]

[CITATION Phi12 \l 1033] proposed the detection of fetal hypoxia during labor using machine learning by building models of the CTG. The models were structured based on the captured patient information, clinical knowledge, and main physiological stimulants of a fetus' heart rate. In the study, the proposed approach focused on interactions between the fetus uterine pressure as the input and the heart rate as the output signals. The two records were used to train the model without enforcing any prior relationships between the two signals. In their findings, the study correctly detected half of the pathological cases within an accepted false positive rate of 7.5%. This allowed for early clinical interventions.

One of the pre-existing intelligent systems used in reducing the risk during labor is the K2
INFANT medical system. INFANT is used in analyzing the strength and quality of the fetus' heart signal by applying the computerized interpretation of Fetal heart rate during labor. Computerized interpretation of fetal heart rate during labor is an artificial intelligence area that is currently on trial. This is an area that promises to improve the reliability and efficiency of fetal heart rate reading by helping them decide the best management based on the reading and ultimately decreasing the burden of work.

[CITATION Ruo19 \l 1033] proposed use of deep convolutional neural networks (CNN) and CNN-based domain transfer learning to automatically recognize 6 standard planes of fetal brains. The study used two datasets one containing 30,000 2D ultrasound images from a sample size of 155 participants between 16 and 34 weeks and the other containing 1,200 image samples through 40 weeks of the pregnancy period. In their findings, the report highlights that deep convolutional neural network demonstrated better performance than the classical deep learning methods. This demonstrated the huge potential of CNN in recognition of fetal brain standard scales.

[CITATION Jin21 \l 1033] proposed a hybrid prediction model of weight at birth. The model was based on long short-term memory (LSTM) networks, The study demonstrated the establishment of a continuous model of parameters relating to the fetal physical examination and the expectant women. The findings of the study showed that the proposed birth weight model increased the prediction accuracy by 6% as well as the model convergence rate by using a hybrid approach.

III.METHODOLOGY

Existing System: Fetal anomaly is defined as a structural or functional anomaly in the fetus that occurs during thepregnancy period and is

INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE

ISSN: 2057-5688

detected prenatally, during or after birth. These defects can complicate pregnancy and cause negative consequences to the developinginfant. Traditional way of dealing with this includes a radiologist analysing the ultrasound scan images of the fetus. However this system comes up with many limitations.
Proposed System: The Proposed System is to develop and evaluate a prototype deep learning model that cananalyze ultrasound scans and detect Congenital Talipes Equinovarus. This research will befocusingontheuseofdeep learning framework, AnomalibinthedetectionofCongenital talipes equinovarus (CTEV). Detection and localization of medical conditions like tumors, haemorrhage, chest infections from radiographic medical images is another massive use case where this framework would be extremely useful. Traditional computer vision algorithms are not effective as the difference between normal samples and abnormal samples can be very small. So, Deep Learning based approaches can automatically learn the difference between normal and abnormal features. Anomalib can be used for detection and localization at a global as well as a local scale. With this one can not only identify different types of anomalies but also highlight local pixel-level anomalous region.

Algorithm

Deep learning belongs to machine learning, in machine learning the feature extraction is carried out manually. But in deep learning, it learns the features automatically. A set of raw images are feed into a deep neural network to learn and obtain the set of all existing features automatically. It is well known that deep learning can provide the best results on a huge volume of data. Since it needs a high-performance GPU. One of the superpowers in computing technology is deep learning. Using deep learning it can be able to make a computer to learn, translate, diagnosis, and so on, on any kind of data such as text, images, signals, and videos. Deep learning is a subset of machine learning it learns, extracts and classifying the features automatically than machine learning. But machine learning extracts features manually.

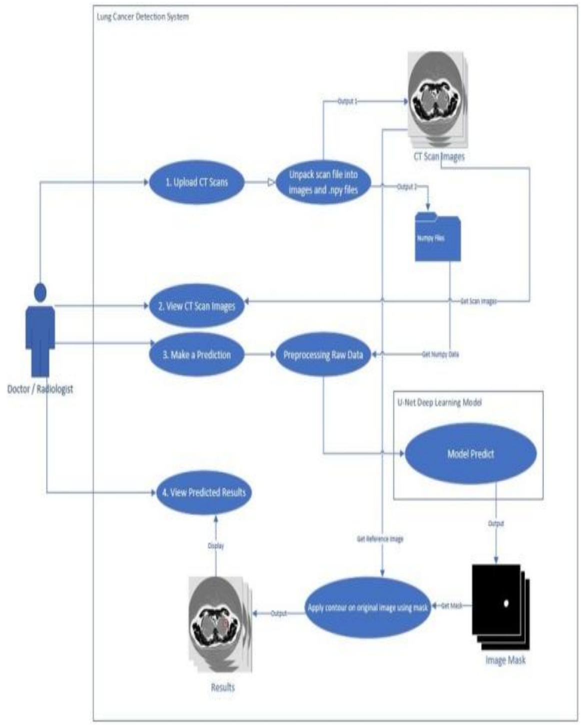

Figure3.1: Architecture diagram

Anomalib is an extensive library for the design, implementation, and deployment of unsupervised anomaly detection models from data to the edge. This framework provides many ready-to-use implementations of anomaly detection algorithms described in the recent literature, as well as a collection of tools that accelerates the development and implementation of custom DL models. This framework has a strong focus on unsupervised image-based anomaly detection, where the objective is to identify outliers in images, or anomalous pixel regions within images in a dataset[1]. Existing anomaly detection libraries focus on single algorithms only, lack performance optimizations, or do not include deep learning techniques [3]. This makes it challenging to utilize these implementations for out-of-the-box comparison of the most recent algorithms on a given dataset. To address these issues, we introduce anomalib, a

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new library that aims to provide a complete collection of recent deep learningbased anomaly detection techniques and tools.

IV. RESULTS AND DISRUPTIONS

Results

Figure5.1 : Input Image 1

Figure5.2 : Ground Truth

Figure5.3 : Predicted Heatmap

Figure 5.4 : Predicted Mask

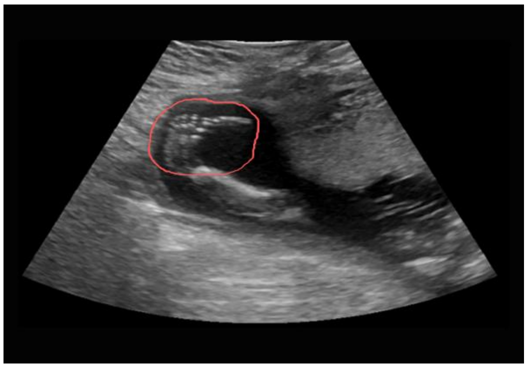

Figure5.5: Segmentation Result

Discussion

A CNN classification model was used for the experiment. The different model metrics were monitored on alterations of the training data and model itself. Among the several alterations that were applied to help improve the performance of the model were: the use of data augmentation, as well as the use of transfer learning. ResNet,an artificial neural network (ANN) of that builds on constructs from pyramidal cells in the cerebral cortex was used in transfer learning. CNN model with transfer learning was selected for implementation because of its high accuracy as compared to the standard model.

V. CONCLUSION& FUTURE SCOPE

The recent developments in AI and deep learning have prompted more medical entities to adopt these technologies to improve their systems and services. These technologies face

ISSN: 2057-5688

a wide range of barriers, including a shortage in specialists, computational resources and public trust, as well as the ability to understand AI. Anomaly detection is a growing research area in machine learning literature, where the goal is to distinguish between normal samples anomalous samples in a dataset. Here, we have used anomalib, a comprehensive library for training, benchmarking, deploying and developing deep-learning based anomaly detection models. In future work anomalib can be extended to other domains such as audio, video, and 3-dimensional data.

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