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An Approach for Fetal Weight Estimation Using Machine Learning for Women Safety

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ABSTRACT

Women safety have its importance in society. women should be safer in all aspects. so here is a model which helps them during their pregnancy. The awareness of health in pregnancy is less in uneducated women. We are building a user-friendly model which can be used by clinicians to identify the risks in of fetus whose effect is usually to carrying mother which linked to each other biologically and as its user friendly it can also be used by patients. Our model is built on considering the fetal health and mother too so that we can avoid the life-taking risk of women and the fetus. As in pregnancy one of the important aspects is knowing the weight of the fetus in the womb. It holds importance to clinicians in the management of pregnancy and delivery by keeping track of the mother's health conditions. As per World Health Organization(WHO), the range of Low Birth Weight(LBW) ranges around less than 2500g, the range of High Birth Weight(HBW) ranges around greater than 4000g, the range of Normal Weight is between 2500g to 4000g. As the fetuses and mothers link to each other biologically, they may both undergo some short and long-term health conditions. To quote some of them are high parent mortality rate, macrosomia as when its High Birth Weight, mental illness in child as long term disorder in Low Birth Weight and chronic diseases in life. To avoid these difficulties we are finding our way in the field of Machine learning and Image Processing concepts. In this paper, we are aiming to develop a model using the Convolution Neural Network(CNN) and a Multiclass SVM algorithm to improve the estimation of fetal weight accuracy and classifying the major disease if the fetus is suffering from a disease which in turn helps clinicians identify the risks before delivery. A balanced dataset is analyzed from zenodo.org. Then these undergo the process of training and classification in two different algorithms for weight estimation and disease classification.

Keywords- Women Safety, Machine Learning, Multiclass SVM, CNN, Fetal weight, Disease Classification

I. INTRODUCTION

Knowing the weight of a baby is important to predict short-term and long-term health outcomes. According to WHO weights are in three different categories: LBW distances (<2500), NBW distances (2500g to 4000g) and HBW distances (> 4000g). To keep this in mind, low birth weight is linked to short-term and chronic illnesses such as Rippiratory Distress Syndrome (RDS) such as short-term and mental retardation, learning disabilities can be considered as long-term disabilities, and much more. In HBW fetros macrosomia is used to describe a newborn baby who is overweight. As described in the HBW range> 4000g, approximately 9% of children worldwide weigh more than 4000g and the risk factor associated with macrosomia increases when the weight exceeds 4500g. Since the baby is at risk of injury such as heart failure, there are also long-term side effects such as low blood sugar levels, childhood obesity. Many risk factors that may increase the risk of fetal macrosomia some can be controlled and some may not. Quoting maternal diabetes mellitus, History of fetros macrosomia, maternal obesity, obesity during pregnancy, having a baby, and much more. Other risks for mothers are labor problems, genital pain, heavy bleeding after childbirth, rupture of the uterus.

The most common way to measure a baby's weight to get an ultrasound is done, because it is safe, not dangerous. Earlier introduced various relay formulas based on different ultrasound parameters. Every setback formula has a problem, it goes there with normal birth weight, but it may not be as accurate as when the baby's weight varies.

According to some studies, for ultrasound, there are many variations related to birth weight such as infant sex, head circumference, maternal age, height, diabetes. It is difficult with a simple traditional withdrawal formula to address multidimensional and non-linear relationships between all of these variables and fetal weight. Recently, a neural implant network (ANN) was used to predict fetal weight to overcome the problems of traditional retinal detachment. Here, we have proposed a separate and predictable birth control model based on training. we collected an estimated data from the default size of the embryo's head using 2D ultrasound images. Then we use

CNN and Multiclass SVM as algorithms where many algorithms are used to divide the embryo into two groups: BW <4000g (LBW, NBW) and WW> 4000g (HBW) Using the GLCM feature extract and the neural convolution network is used as a computer view. , CNN plays an important role and is often used. It pulls out an image element and converts it to a low resolution without losing its element. At the same time, the classification of diseases is also being done. in particular we are considering four main diseases: respiratory disease (RDS), fainting, fetus macrosomia, heart failure so image imaging will be trained and classified for a specific imaging disorder. As a result our model is useful which helps gynecologist to identify the risk before it is too bad and this can be used with a non-medical person (patients) so pregnant mothers can know about their health and the health of the baby and this helps them in the absence of their gynecologist. only ultrasound tests were performed. Sometimes after the ultrasound is done but for the average person to know the details in the ultrasound report is complicated, doctors may not be able to diagnose the emergency in that case — patients can use our model and find out the health status of the baby. We therefore hope that this has a significant impact on women's safety measures.

II. Literature Survey

Here we have made some researches related to our study,
Miao Feng et. al[5] (2019), In this paper the authors have used the traditional techniques of machine learning, the SMOTE and DBN technique were used which are almost limited only for the normal weights. This SMOTE algorithm lacks the variance and generalization which doesn’t make the model accurate one's as they are generalizing the Low birth weight with Normal weight fetus.

Ashley I.Naimi et. al[1] (2018), In this study we observe they have used quantile regression, random forests, Bayesian additive regression, which are simple regression formulas that might have less accuracy compared to our model.

Jia Zheng et. al[2] (2017), In this research, we may know the risk of macrosomia also known as HBW fetus. As per research, the importance of macrosomia ranged from 5% to 20% has increased y 15-20% by last three decades. The maternal complication of the fetus with macrosomia risk may involve complexities such as operative vaginal delivery,c-section emergency, perineal laceration are increased by 4.5times, birth injury, cardiac anomalies, and many more. Infants which are weighing more than 4500g carry the risk of shoulder dystocia, To quote some long-term disorders, they likely to develop obesity, type 2 diabetes. Thus the macrosomia is identified as a worldwide problem.

Maznah Dahlui et. al[4] (2016), In this study, we observe how LWB continues to be the primary cause of infant morbidity and mortality. In this research also they have used the logistic regression analysis which is usually used for surveying the factors. when researched with multiple logistic regression the significant odd ratios were shown for mothers of the northwest region.

Yu Lu et. al[7] (2019), here in this study, again we found the use of random forest, XG-Boost, and light GBM algorithms which are the simple regression formulas which might be not that accurate as per the report there is a 12 % improvement and decreased error by 3%.

Yueh-Chin Cheng et. al[8] (2012), In this research, the model is built on the parameters of ultrasound which may vary from fetus to fetus as they are not that reliable to be considered, they also training the data randomly using the ANN.

Sareer Badshah et. al[6] (2008), This study revealed the effect of LBW in a fetus. Across the world, neonatal mortality is 20 times more likely for LBW, and as a result of research, it's shown that babies are at increased risk of perinatal mortality and morbidity.

Jinhua Yu et. al[3] (2014), In this paper, they have proposed a method based on the support vector regression which was only proposed to improve the weight accuracy below 2500g the LBW fetus.

So far we discussed the literature, from which we can conclude saying, In previous work they have most of the times used the simple regression formula such as support vector regression, random forest, XG-Boost logistic regression analysis, bayesian additive regression which have one or the other drawback to quote some they proposed to just improve the LBW fetus, some have only made analysis, though the ANN algorithm is used to overcome these aspects its approach didn’t meet the expectations. So to overcome all these aspects, we are building a novel model which works on Convolution Networks(CNN) and Multiclass SVM's as they are very good when we have no idea on the data.

III. DATA COLLECTION

The most crucial aspect of any research is data collection. In our model, we used a dataset of foetal ultrasound images from Automated measurement of foetal head circumference using 2D ultrasound images | Zenodo. The dataset contains approximately 3352 images, 90% of which are for training and 10% for testing. During pregnancy, Ultrasound imaging is used to evaluate the biometrics of the foetus.The foetal head circumference is one of these measurements (HC). The HC can be used to calculate the gestational age and track the fetus's growth. The HC is measured in the standard plane, which is a specific cross-section of the foetal head. According to the research, the HC in the 26th week (end of the midterm) of pregnancy value ranges, such as if the foetus HC is < 18.0cm is considered underweight.>24.0cm is considered overweight, while 18.0 to 24.0cm is considered normal (values may vary +10% to -10%). With this analysis, we differentiated three different folders based on HC values using the training set.csv. Overweight, underweight, and normal people are holding the collection of images. Similarly,We have five more folders with the disease dataset (cardiac anomalies, RDS, seizures, Macrosomia, No disease). Our dataset is now ready to train and classify the weight and disease results for a specific test image.

IV. DISEASES OF FETUS

Here we are considering four major diseases or risk which are to be diagnosed at the earliest of which the fetus may suffer from are CardiacAnomolies, RDS, Seizures, Macrosomia.

Cardiac Anomalies: Common symptoms include:
Newborns may show poor feeding, poor growth, and low birth weight Irregular heartbeat, Cyanosis(bluish skin, lips, or nails)Digital clubbing (changes in nails) Shortness of breath Swelling of tissues or organs Becoming tired too quickly on exertion.

Respiratory Distress Syndrome: RDS stands for respiratory distress syndrome. The rds occurs when the lungs have not yet fully developed and are unable to provide enough oxygen, resulting in breathing difficulties. Diagnosis enables doctors to provide necessary treatment prior to delivery by administering certain steroids to the mother, which eventually helps the foetus develop their lungs and gain some energy so that the foetus This is usually done before 2 to 3 days.

Seizures:Seizures: There are numerous causes of neonatal seizures, including the conditions listed above. Infant seizures are more common in babies who were born prematurely or with a low birth weight.oxygen deficiency just before or during birth, caused by: Difficult labour, Umbilical cord problems, Placenta injury, is another cause of seizures that may or may not indicate a birth injury.

Macrosomia: The term "foetal macrosomia" refers to a newborn who is significantly larger than average. A baby is diagnosed with foetal macrosomia if he or she weighs more than 8 pounds, 13 ounces (4,000 grammes), regardless of gestational age. Approximately 9% of babies worldwide weigh more than 8 pounds, 13 ounces. When a baby's birth weight exceeds a certain threshold, the risks of foetal macrosomia skyrocket.I.e, greater than 9 pounds, 15 ounces (4,500 grams) Fetal macrosomia can make vaginal delivery more difficult and put the baby at risk of injury during birth. Fetal macrosomia also increases the baby's risk of health problems after birth. During pregnancy, foetal macrosomia can be difficult to detect and diagnose. Large fundal height and excessive amniotic fluid are signs and symptoms (polyhydramnios).

V. PROPOSED METHODOLOGY

The proposed system here employs machine learning and image processing techniques to estimate foetal weight and disease, if any, if it is overweight or underweight in conditions. Identifying the foetal risk level is critical, as they can become chronic for both mothers and foetuses. The main goal here is to propose a machine learning solution to improve the accuracy of foetal weight estimation and to assist clinicians identify potential risks before delivery.Our model is user-friendly because it can be used by both clinicians and non-clinicians (patients/non-medical people). They can use this after getting their ultrasound done, and because this is primary information, they can take precautions accordingly in the absence of their specific gynaecologist.

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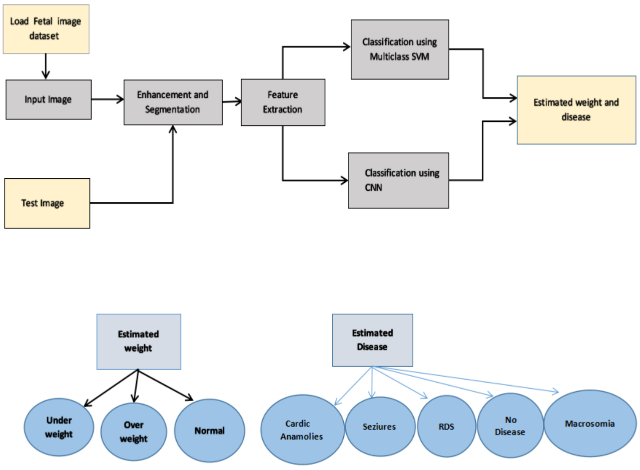

Fig.1. Proposed Methodology

So, we are here using the Convolution Neural Network one of the deep learning models, and the Multiclass SVM as algorithms. In which we consider a balanced data set which contain appx of 3352 image datasets which we have made subfolders of HBW, LBW, NORMAL where each folder contain the set of ultrasound image datasets which will be converted to RGB to GRAY scale images after which the image feature extraction is done which is done using glcm feature extraction with multiclass SVM algorithm, finally we train and classify them. When an input is given, for every input it estimates the weight of the fetus and disease. Along with this we have made real clinical research and collected some sample ultrasound reports of pregnant women who are in the 26th weak of their pregnancy as the fetus start visible in the 26th weak, we are considering BPD, HC, AC, FL of the fetus as these are the judgemental features of a fetus that is the fetus is healthy or not? we are giving the readings of these particular data for input images concerning the weight of the fetus which eventually depends on the HC in the datasets. This helps the mother to be knowledgeable about her fetus in absence of her gynecologist. The results may vary +10% to -10% with given output as they are informative values only.

The model's implementation begins with the loading of balanced datasets into the system, followed by the extraction of features using glcm feature extraction. The data is then stored in the trainmat file, where each feature value is stored, and we use these trainmat files to train our model using multiclass svm and cnn algorithms. The output is classified after the input has been trained and gives output.We finally get the accuracy of both algorithms in terms of percentage by which we can know which outperforms the best.
Finally, we have the accuracy of both algorithms in percentage terms, allowing us to determine which algorithm outperforms the other. One of the most important characteristics used in identifying objects or regions of interest in an image is texture. The texture contains vital information about the surface's structural arrangement. Textural features based on gray-tone spatial dependencies have broad applicability in image classification. Gray level Dependency Matrix is another name for GLCM. It's defined as "a two-dimensional histogram of grey levels for a pair of pixels separated by a fixed spatial relationship." When studying different images, GLCM proves to be a good discriminator; however, no such claim can be made for image quality. As a result, the hunt for the best image quality metric continues. A few examples of common statistics applied to co-occurrence probabilities are discussed ahead.
1)Energy:This metric is otherwise called consistency or precise second. It measures the textural consistency of pixel pair redundancies. It recognizes surface peculiarities. Energy can just have a greatest worth of one. At the point when the dim level dispersion has a steady or intermittent structure, high energy esteems happen. There is a standardized reach for energy. The GLCM of the less homogeneous picture will be enormous of little sections.
2)Entropy:This metric surveys a picture's problem or intricacy. At the point when the picture isn't texturally uniform, the entropy is high, and numerous GLCM components have tiny qualities. Complex surfaces have a high entropy. Entropy has a solid however converse relationship with energy.
3) Difference:
This measurement, which is the distinction snapshot of GLCM, measures the spatial recurrence of a picture. It is the distinction between an adjacent arrangement of pixels' most elevated and least qualities. It tallies the

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quantity of nearby varieties in the picture. A low difference picture has low spatial frequencies and presentations the GLCM focus term around the primary askew.
4)Variance:
This measurement estimates heterogeneity and is exceptionally corresponded with first-request factual factors like standard deviation. At the point when the dark level qualities stray from their mean, the fluctuation increments.
5)Homogeneity:
This measurement is likewise called as Opposite Contrast Second. It estimates picture homogeneity as it accepts bigger qualities for more modest dim tone contrasts in pair components. It is more delicate to the presence of close to slanting components in the GLCM. It has most extreme worth when all components in the picture are same. In terms of identical dispersion in the pixel sets populace, GLCM difference and homogeneity are unequivocally yet conversely related. It implies that if contrast increments while energy stays steady, homogeneity diminishes.
6)Correlation:
the means and standard deviations of gx and gy The relationship highlight estimates the picture's dark tone straight conditions.

A. *Classification*

There are many classification techniques. Here we use the Multiclass SVM and Convolution Neural Network as classifiers individually. The main agenda here is to come up with better classification techniques when compared to other simple regression techniques like random forests, linear regression, logistic regression analysis which have been used in previous work..

Steps for SVM working

1. Image Acquisition
First, we need to select the fetal image and load the fetal image into the system.
2. Segmentation
It means a representation of the image in a more meaningful and easy to analyze way. In segmentation, a digital image is partitioned into multiple segments can be defined as super-pixels.
3. Contrast
Image pixel values are concentrated near a narrow range.
4. Contrast Enhancement
The original image is the image given to the system and the output of the system after contrast enhancement is Enhanced Image, this is the image after removing the sharp edges.
5. Converting RGB to HSI
The RGB image is in the size of M-by-N-by-3, where the three dimensions account for three image planes(red, green, blue). if all the three components are equal then conversion is undefined.
Generally, the pixel range of RGB is [0,255] in his the pixel range is [0, 1]. Conversion of pixel range can be done by calculating the components; Hue, Saturation, Intensity.
6. Extract the GLCM features for the image
GLCM features such as Energy, Entropy, Contrast, Variance, Homogeneity, Correlation, Sum Average, Sum Entropy, SumVariance, DifferenceVariance, Difference, Entropy, Maximum Correlation Coefficient, Information Measures of Correlation1 and Information Measures of Correlation2 are extracted
7. Train the Dataset features
Model = Svmtrain(glcmfeatures, label);
8. Classify the input image
Classifyoutput = Predict(Model, testimagefeature);

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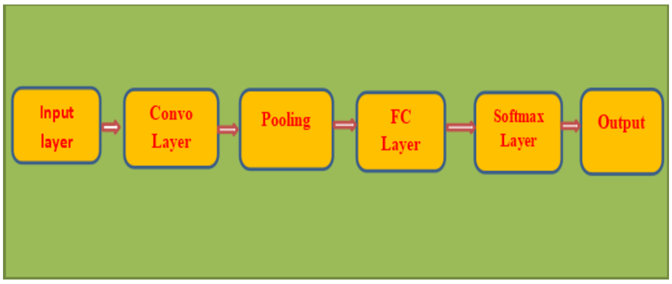

Fig.2. Layers of CNN

Steps for CNN working

1. Load the dataset
2. Train the Model by adding following layers
imageInputLayer(imageSize,'Name','input')
where imageSize = [64 64 3];
convolution2dLayer(3,8,'Padding','same')
batchNormalizationLayer
reluLayer
fullyConnectedLayer(3)
softmaxLayer
classificationLayer];
3. Build aCNN Network Model
net = trainNetwork(datastore,layers,options);
where options = trainingOptions('sgdm', ...
'MaxEpochs',100,...
'InitialLearnRate',1e-4, ...
'Verbose',true, ...
'Plots','training-progress');
4. Classify the Input Image
YPred = classify(net, imdsTest_rsz);
Where , imdsTest_rsz is a test image.

VI. RESULT AND DISCUSSION

In the method of tracking down the best characterization methodology and highlight extraction dependent on picture descriptors and AI strategies the multiclass svm and cnn as a calculation the approx of 3352 pictures dataset are been considered dependent on the dataset 90 of the information has been considered for preparing and 10 for testing the dataset pictures depend on their hc values.

Fig. 3.Trainig in SVM

From, Figure3 we train the dataset, each picture's highlights are been extricated utilizing the GLCM method which is removed.

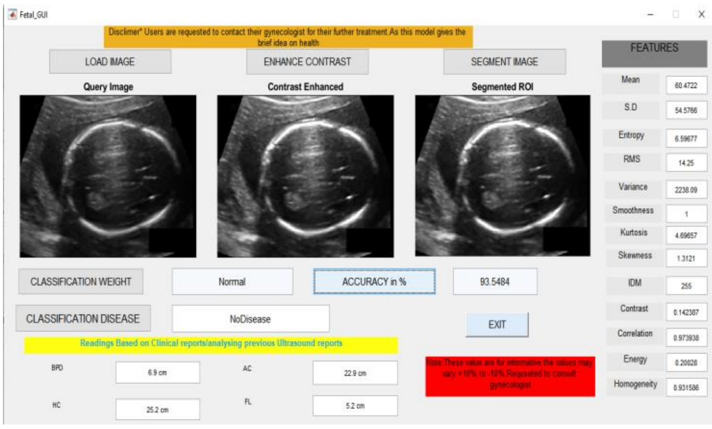

Fig.4.Output of SVM

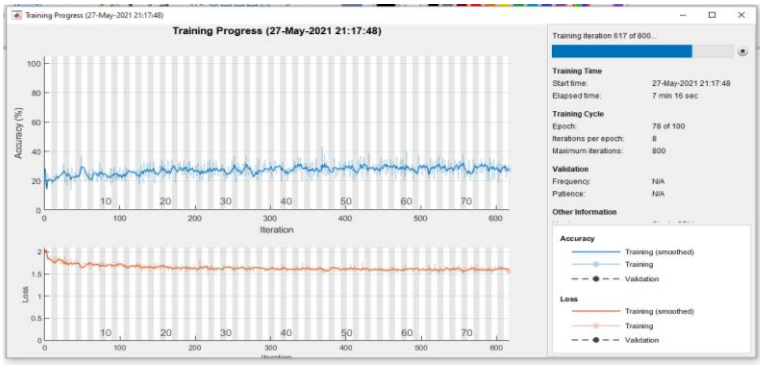

Fig.5.Training in CNN

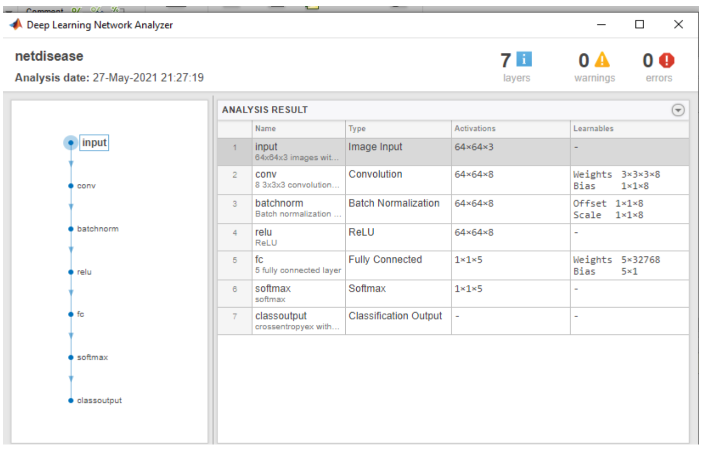

Fig.6. Analysis result of CNN

PAGES: 136-144
9/9/23
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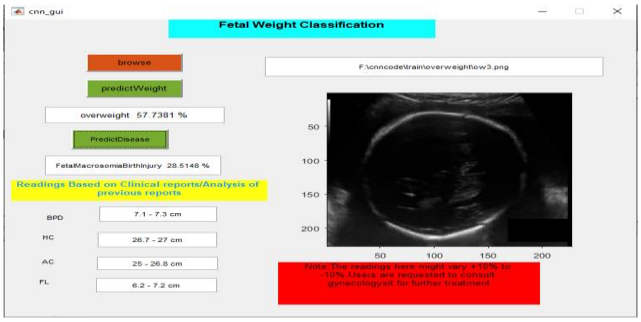

Fig.7. Output of CNN

As shown in Figures 5,6,7, we first trained the datasets; features are extracted by layers, i.e. pixel by pixel, and stored in the Train.mat file, which is then used for classification. The CNN analyzer displays the internal algorithmic structure of the model, allowing us to understand the steps of the algorithm.

As previously stated, women's safety is critical in terms of medical analysis. The goal of this project is to propose a machine learning solution to improve foetal weight estimation accuracy and to assist clinicians in identifying potential risks before delivery.
Following these techniques, we classified the fetus's weight as Overweight,Underweight and Normal, as well as the diseases mentioned above.

Graphical Analysis of Accuracy of Fetal Health


Fig 8.Input Image

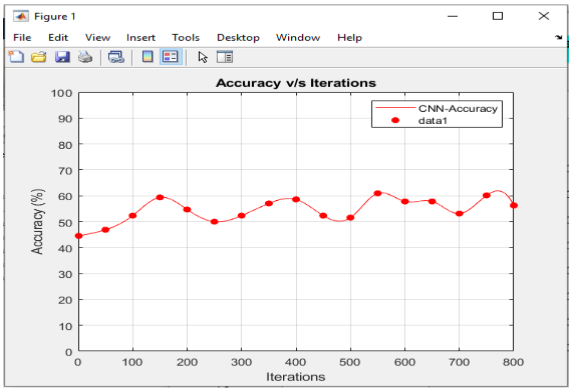

Fig 9.Accuracy in Convolution Neural Network

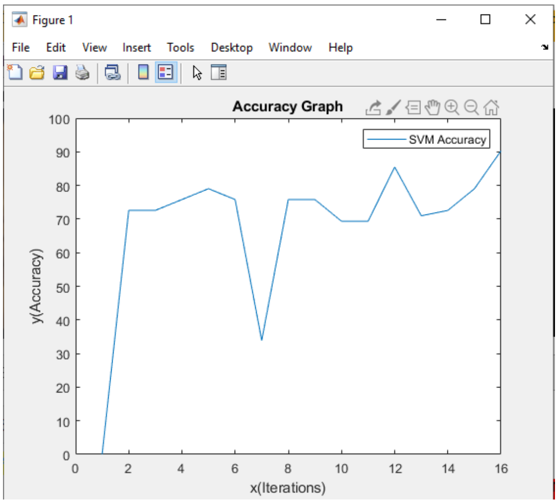

Fig 10.Accuracy in Multiclass svm

Accuracy achieved with the iterations for both the algorithms has been showed above
Using Both Algorithms

- calculate the accuracy witht the Train Data and test Data using formula as shown below
- By Multiclass SVM

accuracy= (Correct(TestDataOutput)/ Total TrainDataoutput)*100

- By Convolution Neural Network

accuracy= (Correct(EachDataOutput)/ TotalTrainDataoutput)*100

- graph has been plotted with the xy plot
- where x axis represnets the iteration count and y axis reprsenst the accuracy value genretaed.

As with the accuracy grpah we can say that multi class SVM has better accuracy than CNN.

VII. CONCLUSION

A classification method has been developed for estimating fetal weight and disease if fetuses are affected. In SVMs, the GLCM technique is used to extract image features. In CNN, layers of images are considered and taken into account. For classification, the proposed method employs both Multiclass SVM and CNN algorithms, with Multiclass SVM outperforming the others.As a result, Multiclass SVM accuracy ranges between 93 and 94 percent, depending on the input image, whereas CNN accuracy ranges between 68 and 70 percent, depending on the image input data. Despite the fact that the system's performance is adequate, we believe that it can be improved further. Incorporating efficient features can help to improve the overall quality.

Future scope

So far, we have used the Neural Network concepts and support vectors here in future it can be built on latest machine learning algorithms in mixture of Artificial intelligence and the data collection can be still more accurate so that the models accuracy gets hiced.

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