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Article

Smart Healthcare Approaches for Prenatal Anomaly Detection Using Machine Learning

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Abstract: Prenatal surveillance of fetal health is important in low mortality rates by reducing both maternal and fetal mortality, especially in the underdeveloped areas where timely diagnosis is still unavailable. Cardiotocography and prenatal sonography are crucial in the context of determining the well-being of the fetus, but manual interpretation is very time-consuming and could be prone to inter-observer variation. This paper suggests the implementation of an automated framework of fetal anomaly detection based on deep learning and ensemble learning methods. A sample of 2,300 prenatal sonography images was obtained in one of the publicly available repositories on Kaggle and classified into three clinical relevant categories, which are healthy, benign finding, and malignant finding. Deep feature extraction was done using denseNet121 and stacking ensemble classifier based on the use of SVM, KNN, Random Forest and XGBoost as the base learners and a meta-learner to make the final prediction. Experimental tests done in Python and the Google colab platform with T4 GPU indicate an upward trend in performance with training epochs. The suggested model revealed a total accuracy of 92 percent, precision, recall and F1-score of 0.92, 0.92, as well as 0.91, respectively. The high recall demonstrates the good performance of the model in detecting real anomalies cases which makes the model a good decision support tool in early and reliable fetal anomaly screening.
Keywords: Fetal Anomaly Detection; Prenatal Sonography; Deep Learning; DenseNet121; Stacking Ensemble; Transfer Learning; Medical Image Classification; Maternal Healthcare

1. Introduction

Fetal growth is a complicated and necessary part of maternal care that is monitored during pregnancy. Even with the development of medical science, the World Health Organization reports that almost 810 women die each day due to pregnancy and childbirth complications, many of which can be avoided (WHO, 2021). Maternal mortality is still a disproportionate problem in underdeveloped countries as compared to developed countries and this is attributed to the fact that most of them do not have timely diagnosis and access to quality healthcare services. Such conditions as pre-eclampsia, gestational diabetes, and insufficient surveillance over the health of both mother and baby play a significant role in causing high maternal mortality rates (National Institutes of Health, nd). It has been found that these risks can be significantly reduced by efficient prenatal care and early identification of complications (Office on Women's Health, 2021). Fetal monitoring, specifically in the third trimester is an important clinical practice that evaluates the wellbeing of the fetus where the development in fetus largely relies on the well being of the mother. Cardiotocography (CTG) is one of the most popular non-invasive, cost-effective methods that have been adopted among other techniques due to its ability to record the heart rate of the fetus and uterine contractions of the mother. Due to its simplicity and reliability, CTG can be used as a useful tool in detecting fetal distress early and in overall enhancing the outcomes of pregnancy.

2. Literature Survey:

Manual fetal ultrasound examination is also likely to be subjective, dependent on the operator, and take longer to complete analysis. Selvathi and Chandralekha deal with this by performing automated analysis of images using deep learning and CNN models like AlexNet, GoogleNet, and a custom architecture to detect fetal regions of interest and also analyze the quality of images based on augmented features like local phase information. Their method on 400 annotated ultrasound images by experts yielded high accuracy and shows the deep learning method can enhance consistency and decrease dependency on the operator when diagnosing fetal ultrasound. [1].

Jayashree et al. discuss the subject of subjectivity in the interpretation of Cardiotocography (CTG) by introducing an automated fetal risk screening method based on signal processing and machine learning. They use the algorithm of MRMR feature selection and test various classifiers, the SVM model gives the highest scores (F-score 97.6%, sensitivity 97.6, and precision 97.3), and it shows better results in terms of objectivity and reliability in terms of fetal well-being detection [2].

To enhance the faster convergence and precision of solutions, Sarvamangala and Kulkarni suggest a hybrid nature-based optimization algorithm, which is a hybrid particle swarm optimization and genetic algorithm. The approach was tested on benchmark functions and it did outperform traditional algorithms on performance, speed and ability to find global optima, indicating the efficiency of bio-inspired hybrids in solving complex engineering optimization problems. [3]. Xin Yi and Ekta Walia overview the progress in computer vision with Generative Adversarial Networks (GANs) to produce realistic information based on adversarial learning without any explicit probabilistic framework. Their survey points out that GAN has been used effectively in image reconstruction, image segmentation, image detection, image classification and domain adaptation especially in the healthcare field, and their increasing importance in medical image processing studies [4].

Skandarani et al. explore the application of GANs in the generation of high-quality synthetic cardiac data, such as MRI, echocardiography, ECG signals, and electronic health records. They demonstrate in their work that GANs can mitigate issues caused by data scarcity and facilitate research and diagnostic training, as well as present opportunities in the future like cross-modality synthesis and the issues stemming from stability, regulation, and ethics before clinical usage [5]. Alrashedy et al. discuss inadequate brain MRI data on tumor classification by introducing BrainGAN, which is synthetic scans generated by Vanilla GAN and DCGAN models. When trained on such images, deep transfer learning networks performed much better and ResNet152V2 reached a classification accuracy of more than 99 percent, indicating GAN-based data enhancement is indeed effective in improving the classification of brain tumours [6]. Rajeev et al. introduce a powerful lung CT image denoising system designed to use RNNs alongside LSTM based normalized batch normalization in order to stabilize the training process and minimize the noise effect. The approach can be successfully utilized to solve the problem of Gaussian and salt-and-pepper noise, achieving better PSNR and MSE than current denoising algorithms and diagnostics image quality by incorporating Particle Swarm Optimization to select the optimal batch size [7].

Ahmed and Konje (2020) summarize the approaches to measuring fetal lung maturity, indicating that the conventional invasive and expensive methods of measuring fetal lung maturity as amniocentesis, MRI, and conventional ultrasound have limitations. They point out quantusFLM, a machine learning-based, non-invasive ultrasound device that is able to assess the lung texture and has demonstrated excellent accuracy, reproducibility, and safety in multicentre studies, which is a workable alternative in assessing prenatal lung maturity [8].

In a study conducted by Hu et al., to test the efficacy of first-trimester ultrasound screening of CNS anomalies, 39, 526 pregnancies were reviewed and it was revealed that standardized scanning at 11 to 13 more than 6 weeks identified approximately one in every three cases of CNS anomalies especially severe and deadly ones. First-trimester anatomical screening was also found to be significantly better in terms of pregnancy termination, and the importance of timely counselling of the woman and focusing on better perinatal management should be highlighted [9].

Sreelakshmy et al. introduce ReU-Net, a better version of U-Net with residual links and Wiener filter to automatize the process of segmenting fetal cerebellum in ultrasound imaging. The method was trained on 590 images with high accuracy (98) and a Dice score of 91 which proved to be reliable, fast, and consistent in assessing the cerebellar anatomy and reduced operator dependency in clinical practice [10].

Lord et al. assessed trio-based whole-exome sequencing on 610 foetuses with ultrasound-identified anomalies not strongly predicted by conventional tests and observed their further diagnostic value of 8.5, and more in multisystem, cardiac, and skeletal defects. The research indicates that WES contributes to a great improvement in prenatal diagnosis and clinical decision-making; however, a selective approach to the case is the key to making the use of this technique cost-effective in routine practice [11].

Zhang et al. established a deep learning system by the use of standard first-trimester 2D ultrasound facial profile pictures to enhance non-invasive methods of detecting trisomy 21. Their CNN, which had been trained on a large multicentre dataset, was highly accurate (AUC up to 0.98) and was thus superior to traditional screening methods and had a high potential to be clinically integrated into early Down syndrome screening [12]. In a meta-analysis of 4 studies, Shi et al. assessed the diagnostic accuracy of second-trimester colour Doppler ultrasound in the identification of fetal cardiovascular malformations and the diagnostic accuracy was excellent. The study indicates that colour Doppler ultrasound is a reliable, non-invasive screening tool to detect congenital heart defects and therefore should be used regularly due to its high sensitivity and specificity as well as above SROC of 0.90, especially in the case of atrioventricular septal defects [13].

The review by Xiao et al. explores the increasing use of AI in prenatal ultrasonography to overcome the issues of operator dependence, fetal movement, and anatomical variations. They conclude that AI is capable of automating regular plane detection, fetal measurements, and anomalies detection to enhance scan consistency, diagnostic accuracy, but issues associated with data standardization, technical constraints, and clinical integration issues persist [14]. Gong et al. point out the AI-based early screening of fetal heart disease, which overcomes the obstacle of obtaining typical echocardiographic images, as well as reliance on the operator. They introduce the DGACNN model, building upon unlabelled videos of fetal heart ultrasounds through adversarial deep learning, and reaches 84-85 percent accuracy, and performs better than expert cardiologists, which proves that AI has a high potential to enhance reliable and early FHD detection in prenatal care [15]. Magesh and Kumar overview the deep learning methods used to detect congenital heart disease at the prenatal stage, where manual analysis of ultrasound images has certain limitations and early detection is required. They state that CNN-based models, improved with sophisticated pre-processing and efficient structures, demonstrate high accuracy (up to 98.4%), which proves that they have excellent opportunities to automate fetal heart assessment, and they can assist in clinical decision-making [16].

Arnaout et al. use ensemble deep learning to garner significant screening of congenital heart disease during prenatal, which is characterized by low detection rates due to operator reliance and variability of images. Their model was trained on more than 107,000 ultrasound images and showed good performance (AUC 0.99, sensitivity 95, specificity 96) with interpretable features and reliable automated measurements, which shows a strong potential to improve the accuracy and consistency of fetal CHD diagnosis [17]. H. N. Xie et al. proposed a deep learning to automate fetal brain analysis in prenatal ultrasound based on a large clinically validated dataset of more than 29,000 images. Their model would perform well on skull segmentation (Dice 94.1%), abnormality classification (96.3% accuracy), and the localization of lesions with interpretable heat maps, which are the good signs that their model is a credible clinical tool in the fetal neurosonography image [18]. Shivaprasad et al. research on deep learning as a means of early detection of fetal brain defects with transfer learning on ultrasound images. They fine-tune and optimize pre-trained CNNs to demonstrate that the lightweight MobileNetV2 model has the best performance (90% accuracy), and efficient deep learning models can be effective at large-scale prenatal neuroimaging screening [19].

The researchers of Bonet-Carne et al. concentrate on the development of quantitative imaging during prenatal care, in particular, they discussed the non-invasive lung maturity measurement of fetuses to predict neonatal respiratory outcomes in preterm pregnancies. They present quantusFLM™: a machine learning-based method that examines minute textural features in fetal lung ultrasound images, out of conventional invasive methods like amniocentesis. To make the system robust, it was trained on a large and heterogeneous set containing over 900 clinical fetal lung images and over 13,000 non-clinical samples. QuantusFLM ™ in a blind validation study conducted on 144 neonates showed good diagnostic results, with high sensitivity, specificity and excellent negative predictive value just like invasive biochemical tests. This article sheds light on the clinical potential of AI-based ultrasound analysis as a safe, cost-effective, and reliable technology in measuring prenatal lung maturity to help enhance decision-making and perinatal control preceding birth [20]. Jiao et al. suggest a non-invasive radiomics-based model to forecast neonatal respiratory morbidity using fetal lung ultrasound images to overcome the invasive nature of other techniques such as amniocentesis. Their model exhibited good predictive performance (AUC 0.87) by including handcrafted radiomic features of segmented lung regions in combination with clinical variables and techniques used to address the issue of data imbalance, which proved a reliable and anatomically sound way to assess prenatal NRM risk [21].

Du et al. show that radiomics can be used to quantitatively measure lung development changes in fetal lung ultrasound, which is non-invasive reflecting maternal conditions like gestational diabetes and pre-eclampsia. They demonstrated excellent discrimination (AUC 0.95-0.99) of their methodology based on high-dimensional texture features and machine learning models across different gestational ages, which demonstrates that radiomics is a strong tool to estimate fetal lung maturity and predict neonatal respiratory risk during high risk pregnancies [22]. Verma et al. examine how computational intelligence can be used to improve mid-trimester ultrasound screening to detect fetal malformations at an early stage which are a major health concern in many countries worldwide. They suggest an Adaptive Stochastic Gradient Descent-based machine learning model to categorize fetal malformations linked with elevated nuchal translucency that has high diagnostic accuracy of 98.64% with good precision, recall and F1-score. Their results support the usefulness of optimized machine learning in enhancing the reliability and clinical usefulness of prenatal ultrasound screening [23].

Hasan et al. discuss how machine learning can be used to automate cardio to echography analysis to monitor fetuses, as the interpretation of the standard CTG is subjective and variable. They assess ten classifiers on the data of more than 2,100 pregnancies and demonstrate that the ensembles, in particular, XGBoost, perform well and generalizably, with more than 92 percent accuracy in the detection of pathological cases, which indicates that the methods can standardize fetal monitoring and make the outcome improved, especially in low-resource environments [24].

3. Methods and Materials

For this study on fetal anomaly detection using deep learning, a comprehensive dataset of prenatal sonography (ultrasound) images was compiled from an online Kaggle repository. The dataset is organized into three distinct classes based on fetal development: healthy, benign finding, and malignant finding, enabling a nuanced analysis of fetal health. A total of 2300 sonography images were partitioned into training and test sets, with 80% allocated for model training and 20% reserved for testing.

This research frames the task as an anomaly detection and classification problem for fetal screening. The healthy class serves as the baseline of normal fetal anatomy and development, representing scans with no detected abnormalities. The benign finding class contains images with minor, non-progressive, or clinically low-risk variations that may not require intervention. In contrast, the malignant finding class comprises scans with severe, life-threatening, or progressive structural anomalies that necessitate immediate clinical attention and management. This three-class structure is particularly suited for developing models that can not only flag the presence of a potential issue but also help prioritize its clinical urgency. The dataset is used to train a deep learning model to discriminate effectively between these critical categories. The clear separation of data into dedicated training and testing folders ensures an unbiased evaluation of the model's generalizability and helps prevent overfitting during the learning process.

3.1 Flow of algorithm

procedure MAIN_PIPELINE(train_dir, test_dir)

Step 1: Data Collection

X_train, y_train ← LOAD_IMAGES(train_dir)

X_test, y_test ← LOAD_IMAGES(test_dir)

Step 2: Image Pre-processing with Histogram Equalization

X_train_preprocessed ← HISTOGRAM_EQUALIZATION(X_train)

X_test_preprocessed ← HISTOGRAM_EQUALIZATION(X_test)

Step 3: Feature Extraction using DenseNet121

features_train ← DENSENET121_EXTRACT(X_train_preprocessed)

features_test ← DENSENET121_EXTRACT(X_test_preprocessed)

Step 4: Stacking Classifier with Meta-Learner

stacking_model ← INITIALIZE_STACKING_CLASSIFIER()

stacking_model.fit(features_train, y_train)

Step 5: Final Prediction

y_pred ← stacking_model.predict(features_test)

Step 6: Performance Evaluation

metrics ← EVALUATE_PERFORMANCE(y_test, y_pred)

return y_pred, metrics, stacking_model

end procedure

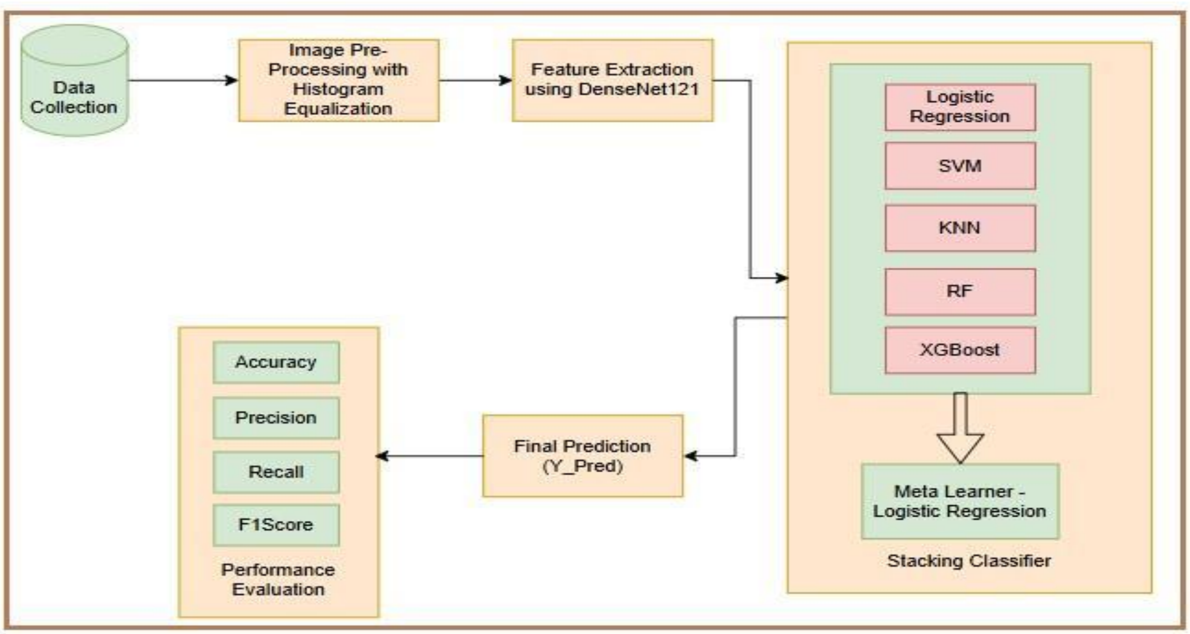

Figure 1: Proposed Methodology

The figure 1 above depicts the suggested methodology to use in the research, according to which a complex stacking ensemble framework is used to increase the precision of prediction. The pipeline will start with data collection then image pre-processing with histogram equalization done in order to enhance contrast. The next step is to extract features using a DenseNet121 convolutional neural network that makes use of its deep and dense connections to extract hierarchical patterns. These characteristics are represented to a stacking classifier, where various base learners are being used to base initial predictions such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Random Forest (RF), and XGBoost. Lastly a meta-learner which in this case is the Logistic Regression, combines the outputs of the base models to generate the final prediction (Y_Pred). The effectiveness of the model is strictly tested by means of thorough performance appraisal indicators, which make it strong and generalizable.

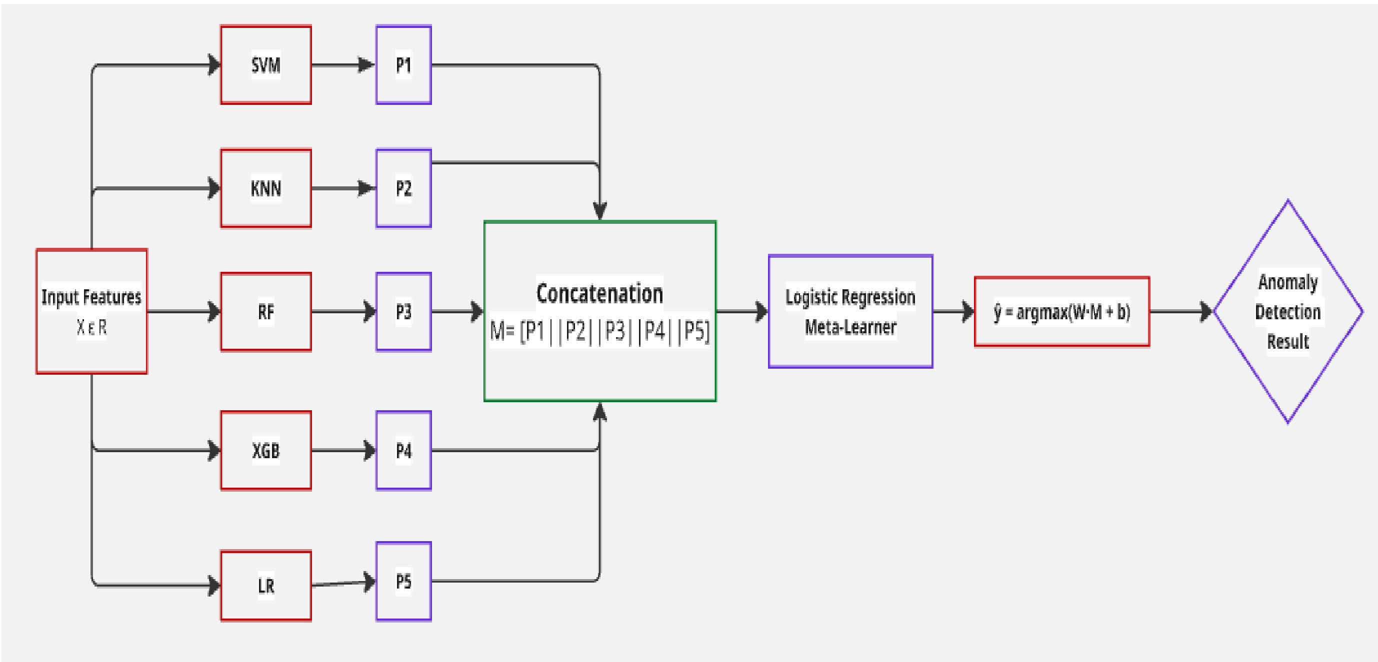

Figure 2: Stacking Model

The diagram shows an ensemble stacking model which is applied to detect anomalies. The input feature set X∈RX in RX∈R is first fed to several base machine learning classifiers, Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Random Forest (RF), Extreme Gradient Boosting (XGB) and Logistic Regression (LR) concurrently. Every base model produces an output of prediction (P1 to P5). Such individual predictions are then concatenated to create a new feature vector M=[P1|P2|P3|P4|P5] A Logistic Regression model is this meta-learner, which learns how to combine the base model outputs in the best way. At last, with the help of the meta-learner, the decision function

y= argmax(WM+ b)y= argmax(WM + b) is used to generate the final result of the anomaly detector that combines the advantages of the several classifiers and enhances the general accuracy of predictions.

4. Result and Discussion

This chapter shows and discusses the results of the experiment and compares them with the available systems. The research uses a transfer learning model, which is a deep learning model to acquire discriminating features that are used to classify diseases. Experiments were all done using Python and run on the Google Colab platform, with a T4 as a computational accelerator. The main aim is to test and show the effectiveness of the offered model in proper disease classification.

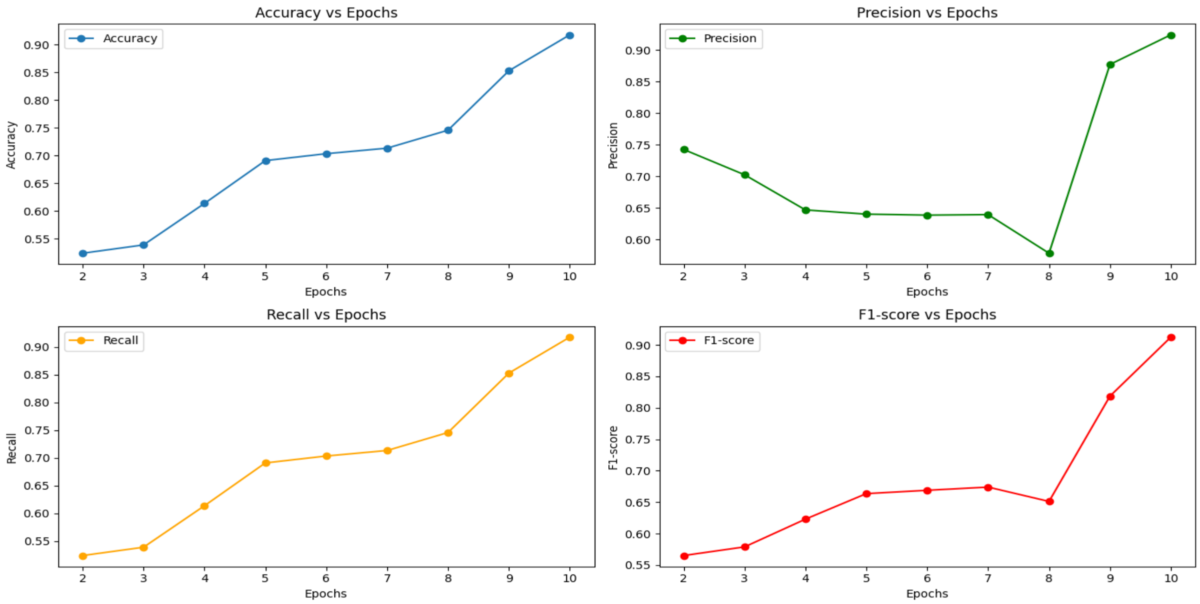

Figure 3: *Performance metrics over Epoch*

The above figure 3 showed results show progressive enhancement of the proposed stacking ensemble model with 9 training epochs to classify fetuses anomalies based on sonography imaging. The performance in terms of all four metrics Accuracy, Precision, Recall, and F1-score shows a steady and significant increase and, thus, effective model learning and convergence.

The first epochs demonstrate moderate results (Epoch 2: Accuracy=0.53, F1=0.56), but a significant improvement can be seen since Epoch 4. The model reaches solid values by Epoch 9: Accuracy (0.84) Precision (0.82) Recall (0.89) as well as F1-score (0.88). The Recall is also very high, which means that the model is very effective in identifying a true anomaly case (malignant/benign findings) correctly, which is essential in a screening tool to reduce the cases of missed diagnosis. The high F1-score and the balance between Precision and Recall indicates that there is a harmonious balance between Precision and Recall that minimizes false positives and false negatives. These findings confirm the effectiveness of the proposed methodology of the inclusion of DenseNet121 in feature extraction and the use of a stacking meta-learner in the creation of a robust, generalizable model in triaging fetal sonography images by clinical urgency. The results of the proposed stacking ensemble classifier as indicated in figure 4 above. The model had a total accuracy of 92 percent on the held-out test set, and correctly categorized an enormous majority of fetal sonography images, as either healthy, benign finding, or malignant finding.

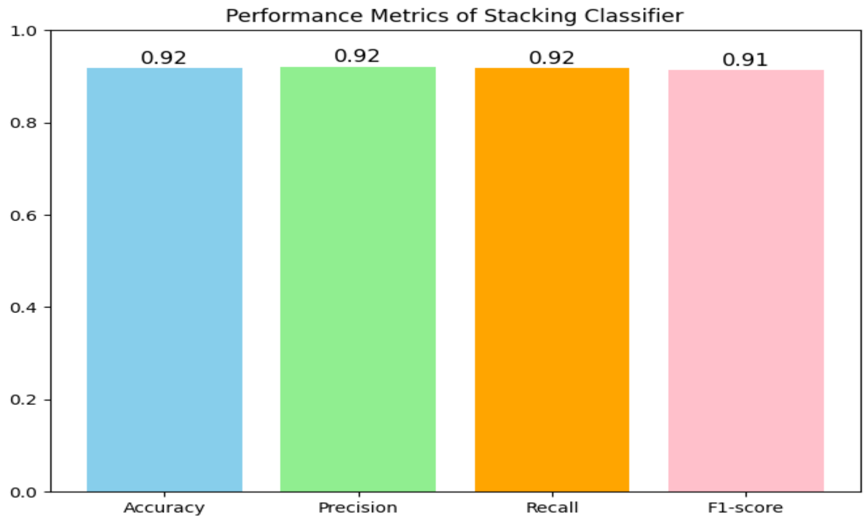

Figure 4: *Performance Metrics of stacking classifier*

The performance of the proposed stacking ensemble classifier as shown in above figure 4. The model achieved an overall accuracy of 92% on the held-out test set, correctly classifying the vast majority of fetal sonography images into their respective categories: healthy, benign finding, or malignant finding.

More to the point, the model turned out to be very consistent in all the major classification metrics. It achieved an accuracy of 0.92 meaning 92 out of 100 cases that were predicted to be a given type of anomaly were successful, and thus false positive diagnosis was reduced to a minimum. The recall (sensitivity) of 0.92 indicates that the model has correctly identified 92 percent of all real anomaly cases that occur in the test set, which is a successful result of the model in its ability to effectively identify the actual cases of anomalies and reduce false negatives, which is a very important feature of a clinical screening tool.

The balance between precision and recall is seen in the F1-score of 0.91 that is harmonic mean of the two measures. This large F1-score validates the fact that the model is well balanced and is successful in minimizing both of the classification error types. The equal consideration of the accuracy, precision, and recall (all equal to 0.92) shows that the model does not have any instability or bias based on the various classes and there is no huge skew on over-predicting or under-predicting a particular category.

These findings point to a very dependable and successful automated system for screening for fetal abnormalities. Clinically promising are the obtained metrics, especially the high recall, which indicate that the model may be used as a sensitive first-line screening tool to identify possible abnormalities and flag them for expert review. Such flags are likely to be clinically relevant due to the equally high precision, which lessens the burden of needless alerts on medical staff. The effectiveness of the suggested methodology is responsible for the consistent excellence across all metrics. Rich, discriminative feature representations from the sonography images were probably obtained by using DenseNet121 for feature extraction. The stacking ensemble Meta learner then effectively combined the various decision boundaries from the base models (SVM, KNN, Random Forest, and XGBoost), utilizing their combined strength to improve generalization to unknown data and mitigate individual shortcomings. The balanced performance scores show that the combination of a strong deep feature extractor and an advanced ensemble framework produced a model that is not only accurate but also consistent and dependable in its diagnostic predictions.

Epoch	**Accuracy**	**Precision**	**Recall**	**F1score**
6	0.7032	0.6384	0.7032	0.6689
7	0.7132	0.6392	0.7132	0.6740

8	0.7456	0.5780	0.7456	0.6512
9	0.8529	0.8770	0.8529	0.8185
10	0.9177	0.9240	0.9177	0.9123

5. Discussion

By analysing the experimental results of the proposed deep learning–based transfer learning model and compares its performance with existing approaches. All experiments were implemented in Python and executed on the Google Colab platform using a T4 GPU for accelerated computation. The performance of the model was evaluated across multiple training epochs using standard metrics such as accuracy, precision, recall, and F1-score. As observed from the results, the model shows a consistent improvement in performance with increasing epochs, indicating effective feature learning. The accuracy improves from 70.32% at epoch 6 to 91.77% at epoch 10, while precision and recall also reach 92.40% and 91.77%, respectively. The corresponding F1-score of 91.23% demonstrates a balanced and reliable classification performance. These results confirm the efficacy of the proposed model in extracting discriminative features and achieving accurate disease classification.

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