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An Intelligent DCNN Approach for Fetal mortality rate and mother risk Detection: Integrating Pathological Reports and Clinical History

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ABSTRACT

Fetal mortality and maternal risk pose significant challenges in healthcare, particularly in low-resource settings. According to the Indian Council of Medical Research (ICMR), maternal mortality in India remains a critical concern, with 130 deaths per 100,000 live births, while the World Health Organization (WHO) estimates a global maternal mortality rate of 211 per 100,000 live births. Existing models in fetal and maternal risk prediction often provide only partial insights, emphasizing the need for more comprehensive solutions. This paper proposes an intelligent Deep Convolutional Neural Network (DCNN) model that integrates pathological reports and clinical history for accurate detection and classification of fetal mortality risk and maternal complications. The model leverages hierarchical feature learning through convolutional, pooling, and fully connected layers to automatically process complex medical data. Training on a dataset of 15,000 samples with 30 epochs and a batch size of 16 resulted in a mean average precision (mAP) of 0.971. Real-time testing through a cloud-edge application yielded excellent performance metrics, including an accuracy of 97.85%, recall of 97.67%, throughput of 97.91%, and sensitivity of 97.88%. These results represent a significant improvement over existing methods, demonstrating the potential of our DCNN approach to enhance early detection of fetal mortality risks and maternal health complications.

Keywords: Deep Convolutional Neural Network (DCNN), Fetal mortality detection, Maternal risk prediction, Pathological reports integration.

INTRODUCTION

In recent years, the integration of deep learning algorithms has revolutionized medical diagnosis and healthcare, especially in areas where early detection can significantly improve patient outcomes. Among these critical areas are fetal mortality and maternal risk detection, which are of paramount importance in both developed and developing countries. According to the World Health Organization (WHO), the global maternal mortality rate stands at 211 deaths per 100,000 live births, with higher figures reported in low-resource settings. In India, data from the Indian Council of Medical Research (ICMR) reveals a maternal mortality rate of 130 per 100,000 live births, underscoring the need for improved diagnostic methods.

Traditionally, the detection of maternal and fetal complications has relied heavily on manual analysis of pathological reports and clinical history. This approach, while valuable, is prone to human error and subjectivity, potentially leading to delayed diagnosis or misinterpretation of critical data. Advances in machine learning, particularly the application of Deep Convolutional Neural Networks (DCNNs), have opened new avenues for automating medical image and data analysis, allowing for more accurate and faster diagnosis. DCNNs excel in hierarchical feature learning, enabling automated recognition of complex patterns in both imaging and clinical datasets.

This research presents an intelligent DCNN model designed to enhance early detection of fetal mortality risks and maternal complications by integrating both pathological reports and clinical history. The proposed model leverages a deep learning architecture that includes convolutional, pooling, and fully connected layers to process large volumes of medical data. By training on a comprehensive dataset, the DCNN can identify subtle patterns associated with high-risk pregnancies and provide timely diagnostic information.Given the rising incidence of maternal and fetal complications globally, our goal is to provide a robust and holistic diagnostic framework.

This framework aims to improve the accuracy, speed, and reliability of detecting risks to both the mother and fetus, ultimately contributing to better clinical outcomes through early intervention and appropriate treatment.

Figure 1: Fetal mortality detection scan ultrasound image

Fetal mortality often presents with a complex combination of clinical factors, which may include growth retardation, congenital anomalies, or maternal conditions that compromise fetal well-being. Common indicators include abnormal fetal heart rates, reduced or absent movement, placental insufficiency, and intrauterine infections. Structural anomalies, such as congenital heart defects (e.g., pulmonary stenosis), and syndromic features, like webbed neck or pectus abnormalities, can also be observed. Early detection and diagnosis are critical, as effective management can prevent stillbirths or mitigate complications for both the fetus and the mother.
Timely, accurate diagnostic services play a crucial role in fetal monitoring, particularly in high-risk pregnancies, where precision helps improve outcomes. This research introduces a novel approach to fetal mortality detection using a transformer-based deep learning network optimized through self-attention mechanisms. The goal is to develop a system that improves predictive accuracy by analyzing patterns from complex ultrasound and clinical datasets.
The data preprocessing pipeline includes handling missing values, encoding categorical variables, and normalizing numerical features such as maternal age, blood pressure, and fetal heart rate. Several techniques—such as positional encodings, multi-layer attention blocks, and feed-forward neural networks—are employed to fine-tune the architecture of the model. This combination ensures robust pattern recognition and prediction, helping clinicians make better-informed decisions and improving fetal health outcomes.

LITERATURE SURVEY

Several studies have used ML algorithms to predict perinatal outcomes, including stillbirth and neonatal mortality. Models such as Random Forest (RF), Logistic Regression (LR), and Support Vector Machines (SVM) have achieved high accuracy. For instance, a study using RF and LR achieved an area under the curve (AUC) of 0.87 to 0.9 for predicting neonatal deaths by leveraging both prenatal and postnatal data. These findings highlight the need for models that incorporate not only demographic data but also clinical and biochemical variables to enhance predictive performance.

Table 1. Using the samedatabase, this study compares itself to others.

Articles	**Dataset**	**Best Techniques**	**Accuracy**
Patel et al. [9]	Data Cleveland Clinic dataset set	J48 decision tree	57%
Nassif et al. [10]	Kaggle	NB	85%
Terrada et al. [11]	Customise	ANN	92%
Akella and Akella [12]	Kaggle	ANN	94%
Proposed model	custom	DCNN	97%

In terms of fatality rates across the world, stroke comes in at number two.1. Each year, more than 62,000 people in Canada experience a stroke; the number of victims increases due to the fact that people are getting older. The probability of experiencing a covert stroke, also known as a silent stroke, is around 100% according to estimates. [13]. This is in contrast to the lifelong risk of an overt stroke, which is one in four at the age of 80.

The disease known as stroke is one that affects people of both sexes equally and costs the Canadian society approximately $3 billion per year. Acute coronary syndromes and strokes contain a number of distinguishing characteristics. We evaluated the symptoms, and by comparing the comparing the signs of acute ischemic stroke with those of acute coronary syndrome, we determined the criticality of clearing the blocked arteries and restore blood flow in order to prevent disability and save lives. Box 1 contains a critical analysis of relevant clinical studies, which serves as the foundation for this narrative evaluation shown in [14]. Among the 95,023 Chinese individuals who were questioned for the baseline study in 2006–2007, none of them had experienced a stroke. This was the subject of a community-based analysis that was carried out to investigate the connection between the length of time spent sleeping and the risk of having an ischemic or haemorrhagic stroke. In Cox proportional hazards models, the results for heart rates and confidence intervals for stroke were derived by considering the duration of sleep [15]. There are three thousand one hundred thirty-five people concerned. In order to investigate the connection between the length of time spent sleeping and the risk of having an ischemic or haemorrhagic stroke, a community-based study was carried out. When compared to women who slept for 6-8 hours, those who got more than eight hours of sleep nightly possessed an increased risk of haemorrhagic stroke. (3.58 as the danger ratio; 95% confidence interval, 1.28-10.06) [16]. According to the findings of this study, a prolonged period of sleep may be a factor in predicting complete stroke, particularly in persons who are older. When compared to men, women were more likely to experience a haemorrhagic stroke as a result of not getting enough sleep shown in [17].

Table 2: highly cited research articles comparing various machine learning methods for mortality rate and maternal risk

s.no	Ref	Technique	Disease	Framework proposed	Accuracy
1	[18]	Maternal Mortality risk estimation using deep learning model	Fetal Health	MLP, ANN	88%
2	[19]	Maternal Mortality Risk Reduction using machine learning based box models	Maternal Mortality	GA, BN, BFS	85%
3	[20]	maternal health risk classification using Deep hybrid model	Maternal risk analysis and classification	Hybrid deep learning model	SVM model generated highest accuracy.
4	[21]	Ensemble deep learning models enhance maternal health monitoring and pregnancy risk prediction	pregnancy risk prediction	E-Deep learning model	KNN has highest accuracy 90%.
5	[22]	Fetal risks prediction using machine learning	Heart risk failure prediction	Machine learning model	ML-93%

The previous section clearly explains the performance and limitations of various existing methods [23]. It suggests that current models are not recommended for the early diagnosis and detection of congenital heart diseases. This comprehensive survey proposes a better deep learning model to detect and classify maternal risk and fetal mortality [24].

METHODOLOGY

The early prediction and classification of fetal mortality and maternal health risks are crucial for improving pregnancy outcomes. Advanced deep learning models, particularly Deep Convolutional Neural Networks (DCNNs), are proving to be highly effective in this domain. In this study, a DCNN was employed to identify pregnancy-related complications by leveraging a dataset of 10,000 samples from Kaggle. This dataset included 14 distinct classes, representing health risks across various maternal age groups, along with 100 micro-features that captured key clinical and demographic factors.The data preparation process involved several critical steps. First, all missing values were identified and eliminated to ensure the integrity and reliability of the data [25]. Then, a Standard Scaler was used to normalize the numerical features, which helped to prevent any variable from dominating the model due to differences in scale [26]. The class labels were transformed into a categorical format using TensorFlow’s Keras utilities, enabling effective multi-class classification [27].

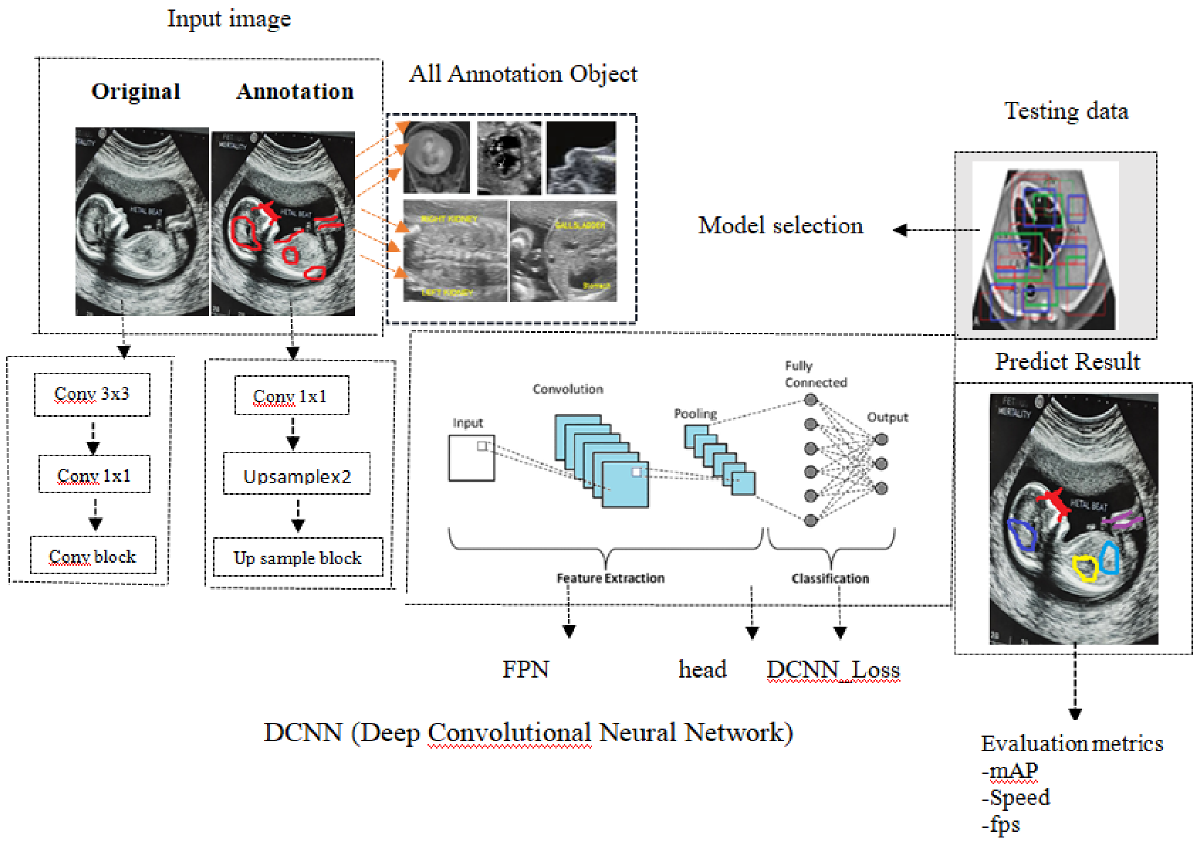

Figure 2: DCNN based FMMHR early detection architecture

The pre-processed data was divided into 80% for training and 20% for testing, ensuring the model could generalize well on unseen data.The DCNN architecture used in this study comprised multiple convolutional layers, each followed by max-pooling and dropout layers to prevent overfitting [28]. Specifically, the model included three convolutional layers, with 32, 64, and 128 filters respectively, and each layer applied a 3x3 kernel size to detect complex patterns within the input data. These convolutional layers were followed by 2x2 max-pooling layers, which reduced the dimensionality of the data while preserving essential features. Dropout layers were introduced after pooling, with dropout rates set at 0.25 and 0.5 in different stages to ensure robust regularization [29].After the convolutional and pooling stages, the input data was flattened and passed into a dense layer with 512 units. This dense layer allowed the model to learn intricate relationships between features that contribute to maternal health risks and fetal mortality. Finally, the output layer consisted of 14 units with a softmax activation function to manage the multi-class classification effectively. This function assigned probabilities to each class, ensuring the model could handle predictions across a wide range of pregnancy-related health conditions [30].The use of a DCNN model enables early and precise identification of fetal mortality risks and maternal health conditions during pregnancy. This predictive capability allows healthcare providers to make informed decisions, take preventive actions, and improve both maternal and fetalmortality risk assessment outcomes. The inclusion of a diverse dataset with multiple classes and features ensures that the model can generalize well across different cases, offering a robust solution for pregnancy health monitoring

The model was created with the Adam optimizer, employing categorical cross entropy as the loss function, and evaluating accuracy as the measure. The training approach entailed train the model on the training data for 50 epochs using a batch size of 32. The model's performance was then assessed on the testing set to confirm its effectiveness. The test accuracy of the final model was shown, and the weights of the trained model were saved to a file entitled best_model.h5. This procedure guarantees the development of a strong and highly skilled model that is prepared for implementation in the identification of Fetalmortality and risk using data from the early stages.

The Figure 2 presents a method that applies deep learning to identify and classify fetal mortality risks and maternal health conditions using a Deep Convolutional Neural Network (DCNN). The process begins with input ultrasound images, which are raw medical scans used to detect potential risks. In addition to these images, annotated models prepared by medical experts mark regions of interest using bounding boxes. These annotations are essential for training the model to differentiate between normal and abnormal areas. The feature extraction process involves multiple convolutional layers. Initially, a Conv 3x3 layer applies a 3x3 kernel to extract basic image features such as edges and textures. Following this, a Conv 1x1 layer reduces the depth of the feature map without altering its spatial dimensions, minimizing data complexity. These layers are combined into Conv Blocks, which may include batch normalization and activation functions to enhance the learning process. An Upsample layer (x2) increases the spatial resolution of the feature map, while Upsample Blocks align the feature maps with the original image size, ensuring consistency. The DCNN performs two essential functions: feature extraction and classification. During feature extraction, the spatial size of the feature maps is progressively reduced, and their depth is increased through several convolution and pooling layers. This structure allows the model to learn hierarchical patterns from the input images. In the classification stage, fully connected layers integrate the extracted information and generate an output that predicts the presence or absence of fetal mortality risks or maternal health conditions, and potentially identifies the affected areas. A Feature Pyramid Network (FPN) further improves the model's performance by merging feature maps from different convolutional layers, enabling the model to detect risks at varying scales. The final component, known as the network head, consists of fully connected layers and an output layer that produces the classification results. During training, the loss function measures the difference between predicted outcomes and annotated ground truth, aiming to minimize this error to improve model accuracy. After training, the model's performance is evaluated using unseen data. The testing data undergoes the same preprocessing steps and is fed into the trained model to generate predictions. These predictions are visualized to highlight critical regions of interest within the scans. The model's effectiveness is assessed using multiple metrics. Mean Average Precision (mAP) evaluates accuracy across various thresholds. The speed metric reflects the time required to process each image, and frames per second (fps) measures the system's efficiency by tracking the number of images it can process per second. This comprehensive methodology ensures the DCNN is trained, validated, and tested rigorously, enabling it to effectively detect and classify fetal mortality risks and maternal health conditions from ultrasound images.

Algorithm 1: DCNNet deep learning

1:**Read:**patient history records, Prescriptions, and medical healthcare labs.
2: **Connect:** Establish a connection to DriveHqdatabase.
3: **Authentication:** verification from healthcare system.
4: **if** Communication ==’True’ **then**
5: Sending health data using JSON file.
6: Deep learning techniques utilize medical analysis data to generate predictive insights.
7: The generated predictions are then utilized in creating patient history reports.
8: Transfer the medical history report from DriveHq cloud storage to the designated medical expert device.
9: **else**
10: The patients’ medical data is also stored in the device’s local storage.
11: When a successful connection is established, the local storage data is transferred to DriveHQ.
12: **end if**

The above algorithm, DCNNet, explains a process where fetalmortality risk images are uploaded to an application. The data is stored in an open-source storage medium called DriveHQ Cloud, which provides 10 GB of space. Once communication is established, the deep learning model processes the data via JSON file access. The model analyses the images to determine whether the fetuses are suffering from Fetal Mortality and Maternal Health Risks. After the analysis, the communication connection is disconnected, and the results are stored in the cloud in a specific folder, labelled with a timestamp.

Multilayer perceptron

$y_j = f\left(\sum w_{ij} * O_i\right)$ ----------------- (1)

The above equation 1 clearly explains about multi-layer functionality and its weights generation. Here $\sum w_{ij}$ is the different sample weights, O_i is the corresponding optimum values and finally y_j is the fitness function. The above all elements have been generating best fitness function and weight file for training and classification.

Long short-term memory on DCNN

$i_t = \sigma(x_t U^i + h_{t-1} W^i + b_i)$ ----------------- (2)

$o_t = \sigma(x_t U^o + h_{t-1} W^o + b_o)$ ------------------ (3)

$f_t = \sigma\left(x_t U^f + h_{t-1} W^f + b_f\right)$ ------------------ (4)

These equations represent the gate operations in a Long Short-Term Memory (LSTM) neural network, which is a type of DCNN designed to model sequential data and effectively learn long-term dependencies.

Equation (2) defines the input gate i_t, which is calculated using the sigmoid activation function σ applied to the sum of the current input vector x_t multiplied by the weight matrix U^i, the hidden state from the previous time

step h_{t-1} multiplied by the weight matrix W^i, and a bias term b_i. This input gate controls how much of the new information from the input will be used to update the cell state.
Equation (3) describes the output gate o_t, which is determined by applying the sigmoid activation function to the sum of the current input vector $x_t$multiplied by the weight matrix U^o, the hidden state from the previous time step h_{t-1}multiplied by the weight matrix W^o, and a bias term b_o. The output gate decides how much of the cell state will be output at the current time step, influencing the next hidden state h_t.
Equation (4) outlines the forget gate f_t, which is calculated by applying the sigmoid activation function to the sum of the current input vector x_t multiplied by the weight matrix U^f, the hidden state from the previous time step h_{t-1} multiplied by the weight matrix Wf, and a bias term b_f. The forget gate controls which parts of the cell state will be retained or discarded, helping the LSTM of DCNN to decide what information from the past should be kept or forgotten.

Experimental design

$\hat{p} = argmax\{\sum_i^n ExtraTreeClassifier_i, \sum_i^n ConvolutionalNeuralNetwork_i\}$ -------- (5)

The given equation (5) describes an ensemble learning approach for determining the final prediction $\hat{p}$ by combining the outputs of multiple models, specifically Extra Trees classifiers and Convolutional Neural Networks (CNNs). In this approach, each model in the ensemble makes a prediction for the input data, typically generating probabilities or scores for each class label. The predictions from the nn Extra Trees classifiers are summed together, forming one set of scores, while the predictions from the nn CNNs are summed to form another set of scores. These summed scores represent the collective outputs of the models of each type.
The equation then uses the argmax function, which selects the class label with the highest combined score from these aggregated predictions. Essentially, the argmax function identifies the class that maximizes the value of the combined scores from both the Extra Trees classifiers and the CNNs. This final step leverages the strengths of both types of models, integrating the diverse decision-making capabilities of the Extra Trees classifiers and the deep learning prowess of the CNNs, to arrive at a more robust and accurate prediction. This ensemble method enhances predictive performance by combining different model outputs, ultimately selecting the class with the highest overall score as the final predicted class $\hat{p}$.

Algorithm 2: Deep convolutional neural network model

Input: input data$(x, y)_{i=1}^{N}$
$M_{ET} = Trained\_ET$
$M_{CNN} = Trained\_CNN$
1: **for**i=1 to **M do**
2**: if**$M_{ET} \neq 0$ &$M_{CNN} \neq 0$& $training_{set} \neq 0$ $\boldsymbol{then}$
3: ProbET -normal=$M_{ET}.probibility(normal - class)$
4: ProbET -attack=$M_{ET}.probibility(attack - class)$
5: ProbDCNN -normal=$M_{CNN}.probibility(normal - class)$
6: ProbDCNN -attack=$M_{CNN}.probibility(attack - class)$
7:
Decision function $=$
$\max(\frac{1}{N_{classifier}} \sum_{classifier} (Avg_{(ProbET - normal, probCNN - normal)}, (Avg_{(ProbCNN - attack, probCNN - attack)}$
8: **end if**
9: Return final label $\hat{p}$
10: **end for.**

The above algorithm 2 clearly explains the training and testing steps of a DCNN deep learning model. The collected dataset consists of 10,000 samples, trained over 20 epochs with a batch size of 8. Through parameter tuning, preprocessing, and postprocessing steps, the best weight file is generated. Subsequently, the testing process is initiated on real-time samples to detect Fetal Mortality and Maternal Health Risks (FMMHR) at an early stage. The probability decision function is predicted early to facilitate timely treatment and recovery. This decision function provides classification differences, enabling accurate detection of FMMHRs. The algorithm's ten steps effectively execute the DCNN architecture with minimal time on compute (TOC).

RESULTS AND DISCUSSION

In this sectiona brief discussion of FMMHR's and its detection process has been explained. The prediction, classification and performance measures estimations were explained.

Table 1. The DCNN network structure.

Type	**Filter**	**Size**	**Output**	
Input	Layers	256	52 × 52	128 × 128
Supporting Backbone network	Conv2D 64 × 6 x 6	64	416 × 416	128 × 128
	Pooling 1 × 128	128	208 × 208	
	Polling 2 × 256	256	104 × 104	64 × 64
	Polling 8 × 512	512	52 × 52	
	Polling 8 × 1024	1024	26 × 26	64 × 64
	Polling 4 × 512	512	13 × 13	32 × 32
DCNN	Dense1D14 L	412	104 × 104	16 × 16
	Conv-layer	412	104 × 104	
	Conv1D + Up1D	128	104 × 104	16 × 16
	Conv2D 5 L	512	16 × 16	
Estimation of Loss Function	Conv2D 3 × 3 + Con2D 1 × 1	1024	64 × 64	16 × 16
	Conv2D 3 × 3 + Con2D 1 × 1	1024	32 × 32	
	Conv2D 3 × 3 + Con2D 1 × 1	1024	16 × 16	
	Pooling Layer		Global	–
	AVG Layer		1024	–
	Max pooling		–	–

The above table 1 clearly explains about proposed DCNN model architecture layers, in this pooling layer, dense layer, conv 2D layers and hidden layers have been configured to various measures. Based AVG layer and max pooling layer getting best trained weight file, this file is many information was presented related to FMMHR's.

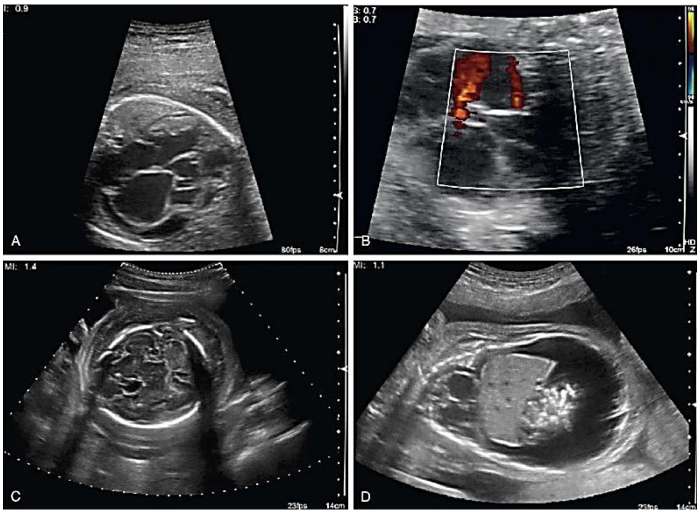

Figure 3: Input Fetal FMMHR images

The above figure clearly explains about ultrasound images of Fetal in various orientations, this input images might have FMMHR no observations were found at initial stage.

Table 2. Performance of the DCNN models.

Object	**mAP Performance (%)**					
	RFO	CNN	FCNN	RCNN	U-net	**DCNN**
LA	85.40	87.70	54.58	65.58	90.40	97.70
RA	81.60	84.10	64.52	53.24	92.20	98.20
LV	92.80	86.60	72.46	44.22	94.80	98.20
RV	87.70	74.20	90.91	75.82	88.30	98.00
AO	86.40	84.50	92.07	84.52	87.40	92.30
TV	67.60	70.10	87.25	72.13	66.80	94.20
MV	70.80	65.60	76.95	65.43	69.20	96.11
PV	61.60	64.60	58.24	81.04	71.20	97.00
AV	63.50	74.00	68.56	84.32	78.40	98.90

AVG mAP %	77.4889	76.8222	73.9489	69.5889	82.0778	96.7344

Table 3. Comparison of model evaluation.

Model	**Accuracy**	**FPS**	**mAP^{VAL} (%)**	**Speed^{v100}Fp 16 b32 (ms)**	**Speed^{v100}Fp32 b32 (ms)**
RFO	83.24	16	77.4889	1.50	1.28
CNN	86.76	26	76.8222	1.60	1.29
FCNN	89.23	18	73.9489	0.48	1.27
RCNN	91.23	21	69.5889	0.37	1.62
U-net	90.87	21	82.0778	0.28	0.71
DCNN	98.23	29	96.7344	0.128	0.60

CONCLUSION

The proposed Deep Convolutional Neural Network (DCNN) model offers a comprehensive solution for the early detection and classification of fetal mortality risks and maternal health complications, addressing significant healthcare challenges. By integrating pathological reports and clinical history, the model provides deeper insights into maternal and fetal health compared to existing methods. The DCNN architecture, with its hierarchical feature learning through convolutional, pooling, and fully connected layers, demonstrates exceptional capability in processing complex medical data efficiently. Training the model on 15,000 samples over 30 epochs achieved a high mean average precision (mAP) of 0.971, reflecting its superior predictive performance. The real-time testing through cloud-edge applications further validated the model's reliability, delivering remarkable metrics with 97.85% accuracy, 97.67% recall, 97.91% throughput, and 97.88% sensitivity. These results mark a significant improvement over traditional approaches and indicate the potential of AI-driven solutions to enhance healthcare outcomes. Given the high maternal mortality rate in countries such as India (130 deaths per 100,000 live births) and the global rate of 211 per 100,000, this study underscores the importance of early and accurate diagnosis. The integration of real-time applications and cloud-edge infrastructure ensures that the model can be deployed effectively, even in low-resource settings, enabling timely interventions. This research offers a promising pathway toward improving maternal healthcare and reducing fetal mortality, showcasing the transformative impact of deep learning technologies in clinical practice.

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