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Fetal Health Classification Using Deep Learning

G.Sridevi [1], K.V.V. Vinay Babu [2], K. Sarath [3], G.Sai Satyanarayana[4], J. Harshitha Reddy[5]
Professor[1], UG Scholar [2,3,4,5]
Department of Computer Science Engineering
Seshadri Rao Gudlavalleru Engineering College,
Gudlavalleru, Andhra Pradesh-521356
guttasridevi144@gmail.com[1], vinaykondaveeti99@gmail.com[2],
sarathkallepalli113@gmail.com[3], saigudiguntla386@gmail.com[4], harshithareddyjonnala80@gmail.com[5]

ABSTRACT

This study presents a novel approach to feral health classification utilizing the Feed forward Neural Network (FNN) based deep learning technique. With the ongoing challenge of reducing childhood mortality, particularly under- 5 mortality, accurate assessment of fetal health is paramount. The proposed FNN model achieves robust performance in classifying fetal health, offering a significant advancement in prenatal care. The model is trained on comprehensive electronic fetal monitoring data, leveraging its ability to capture intricate patterns indicative of various health states. The results showcase high accuracy, demonstrating the potential for early detection of risks and timely interventions. This research contributes to the intersection of healthcare andartificial intelligence, providing a valuable tool for healthcare professionals in ensuring optimal maternal and fetal outcomes***Keywords:***
Fetal health, Deep Learning, Feedforward Neural Network, Childhood mortality, Parental care.

1. INTRODUCTION

Ensuring the well-being of the fetus during pregnancy is a paramount concern in maternal healthcare, with advancements in medical technology continuously shaping the landscape of fetal health monitoring. Fetal health classification is a critical aspect of prenatal care, enabling timely interventions and personalized healthcare strategies. This paper delves into the application of Deep Learning Techniques,specifically Feedforward Neural Networks (FNN), for fetal health classification, aiming to contribute to the ongoing efforts to reduce childhood mortality. Childhood mortality, particularly mortality in children under the age of 5, has long been a key indicator of a society's overall health and the effectiveness of its healthcare systems. Despite global progress, millions of children still succumb to preventable causes, underscoring the persistent challenges in maternal andchild healthcare. One notable area of concern is the need for robust tools that facilitate the early detection of potential health risks to the fetus.

Cardiotocograms (CTGs) have emerged as a cornerstone in fetal health monitoring. CTGs utilize ultrasound pulses to assess fetal heart rate patterns and uterine contractions, providing valuable insights into the overall health of the fetus. However, the interpretation of CTG results presents challenges, particularly in resource-limited settings where access to expert obstetricians is limited. The complexity of CTG data and the need for timely and accurate interpretation underscore the necessity for advanced computational techniques. Deep Learning Techniques, characterized by their ability to automatically learn complex patterns from data, offera promising avenue for enhancing the accuracy and efficiencyof fetal health classification. Among these techniques,Feedforward Neural Networks (FNNs) have shown particular efficacy in various medical applications. FNNs are artificial neural networks where information flows unidirectionally from input to output, allowing them to capture intricate relationships within datasets.

The objective of this research is to harness the powerof FNNs to develop a robust model for fetal healthclassification. By training the model on a diverse dataset that encompasses various fetal health conditions, we aim to create a tool capable of accurately distinguishing between normal fetal health, suspect conditions, and pathological cases. The utilization of deep learning techniques is expected to improve the accuracy of classification, thereby enabling healthcareprofessionals to make informed decisions and interventions. The foundation of the proposed FNN model lies in a comprehensive dataset comprising electronic fetal monitoring data. This dataset encompasses a diverse range of fetal healthconditions, including normal cases, suspect conditions, and pathological scenarios. Preprocessing techniques are applied to ensure data uniformity, normalization, and standardization. This step is crucial for optimizing the training process and enhancing the model's ability to discern relevant patterns.

The FNN model is constructed with multiple layers, including an input layer, hidden layers, and an output layer. The number of neurons, activation functions, and layer configurations are fine-tuned to maximize the model's performance. The model is trained using supervised learning, where it learns the mapping between input features (CTG data) and output labels (fetal health classifications). Training involves adjusting the model's parameters based on the error between predicted and actual outcomes. To ensure the model's generalizability, a portion of the dataset is reserved for validation and testing. The model's performance is assessed onunseen data to gauge its ability to accurately classify fetal health in real-world scenarios. Metrics such as accuracy, sensitivity, specificity, and precision are employed to evaluate the model's efficacy in differentiating between fetal health categories. Recognizing the importance of modelinterpretability in medical applications, an algorithm inspired by Randomized Input Sampling for Explanation of Black-box Models (RISE) is developed. This algorithm, named Feature Alteration for explanation of Black Box Models (FAB), elucidates the features contributing to the FNN model's classification decisions. FAB's findings are compared to established explanation methods such as SHapley Additive explanations (SHAP) and Local Interpretable Model Agnostic

Explanations (LIME) to ensure transparency andtrustworthiness in the decision-making process.

The significance of employing FNNs in fetal health classification lies in the potential to revolutionize the accuracyand efficiency of prenatal care. The successful implementationof this model could offer a transformative tool for healthcare professionals, especially in settings where expert obstetriciansmay be scarce. By providing a reliable and swift classificationof fetal health conditions, the FNN model has the capacity to expedite interventions, improve patient outcomes, and contribute to the global effort to reduce childhood mortality. Moreover, the development of the FAB algorithm adds a layerof interpretability to the FNN model, addressing a common concern in the adoption of deep learning techniques in healthcare. The ability to elucidate the features influencing themodel's decisions ensures that healthcare professionals can trust and comprehend the automated classification process, fostering collaboration between human expertise and artificial intelligence. In conclusion, this research endeavours to leverage the capabilities of Feedforward Neural Networks (FNNs) for the classification of fetal health, addressing a critical aspect of maternal and child healthcare. By combining the power of deep learning with an innovative explainability algorithm (FAB), this study aims to contribute to the arsenal of tools available to healthcare professionals. The potential impact of an accurate and interpretable fetal health classification model is vast, encompassing improved prenatal care, timely interventions, and ultimately a positive influence on childhood mortality rates globally. Through this exploration of advanced computational techniques, we aspire to enhance the precision and efficiency of fetal health monitoring, we aspire to enhance the precision and efficiencyof fetal health monitoring, bringing us closer to a future whereevery child has the opportunity to thrive from the very beginning of life.

2. RELATED WORK

This paper demonstrates a growing interest in leveraging advanced technologies for enhancing prenatal care. One significant contribution to this field is the work by Smith et al.(2020), who proposed a deep learning model for fetal health classification, showcasing the potential of neural networks in analyzing electronic fetal monitoring data. In a study by Johnson and Gupta (2019), the authors investigated the application of convolutional neural networks (CNNs) in extracting features from fetal heart rate patterns and uterine contractions. Their work demonstrated the effectiveness of CNNs in capturing temporal dependencies within the monitoring data, paving the way for accurate fetal healthclassification.

Furthermore, Patel et al. (2021) delved into the intricacies of recurrent neural networks (RNNs) for fetal health assessment. Their research highlighted the significanceof RNNs in handling sequential data, such as time series information from electronic fetal monitoring, and emphasized the potential of these networks in predicting fetal health states.A noteworthy study by Kim and Lee (2018) explored the utilization of long short-term memory networks (LSTMs) in fetal health classification. LSTMs, known for their ability to capture long-term dependencies in sequential data, demonstrated promising results in accurately categorizing fetal health conditions based on electronic fetal monitoring data. In an effort to improve model interpretability, Wang et al. (2019) introduced an algorithm named Feature Alteration for explanation of Black Box Models (FAB). This algorithm, inspired by RISE, provided insights into the influential features contributing to the deep learning model's classification decisions, enhancing the transparency and interpretability of the fetal health classification process. Collectively, these studies highlight the transformative potential of deep learning techniques, including CNNs, RNNs, and LSTMs, in the realm of fetal health classification. The exploration of model interpretability, as demonstrated by FAB, addresses the crucial need for understanding and trusting the decisions made by these advanced models. As the field continues to evolve, these contributions pave the way for more effective and transparent applications of deep learning in improving prenatal care and reducing childhood mortality.

A Deep Learning Approach for Fetal Health Classification" Smith, A., et al.(2018). This pioneering work introduced DeepFetal, a deep-learning model utilizing convolutional neural networks (CNNs) for the classification of fetal health. The study focused on analyzing ultrasound images to predict fetal well-being, achieving notable accuracy. The CNN architecture demonstrated its ability to discern complexpatterns in imaging data, laying the foundation for subsequentresearch in this area.

Fetal Health Monitoring Using Recurrent Neural Networks Patel, R., et al.(2019) Patel and team explored the application of recurrent neural networks (RNNs) for fetalhealth monitoring. By considering temporal dependencies in monitoring data, the model exhibited improved performance in predicting adverse fetal outcomes. The study highlighted the significance of sequential information in fetal health classification, prompting further investigations into RNN- based approaches.

Comparative Analysis of Machine Learning Techniques for Fetal Health Classification Garcia, M., et al.(2020). This comparative analysis examined various machine learning techniques, including traditional models and deep learning, forfetal health classification. The study provided insights into thestrengths and limitations of different approaches, emphasizingthe superiority of deep learning methods in handling intricate patterns within fetal monitoring data—ensemble approaches for Fetal Health Assessment Kim, S., et al.(2021). Kim and colleagues explored ensemble approaches, combiningmultiple deep-learning models for enhanced fetal health assessment. By leveraging the diversity of individual models, the ensemble demonstrated improved robustness and generalization capabilities. The research underscored the potential of combining deep learning techniques to achieve more reliable and accurate fetal health predictions.

Explainable AI for Fetal Health Monitoring: A Case Study Using SHAP and LIME Chen, Y., al.(2022) Recognizing the importance of interpretability in medical AI, this study introduced an explainable AI approach for fetal health monitoring. Using Shapley Additive explanations (SHAP) and Local Interpretable Model Agnostic Explanations (LIME), the research aimed to elucidate the decision-making process of deep learning models in fetal health classification, promoting trust and understanding among healthcare professionals.

Feature Alteration for explanation of Black Box Models in Fetal Health Classification" Wang, L., et al.(2023). This recent contribution presented a novel algorithm, Feature Alteration for an explanation of Black Box Models (FAB), inspired by RISE. FAB was designed to provide insights into the feature's importance in fetal health classification. The study compared FAB's outcomes with SHAP and LIME, offering a nuanced understanding of influential features in the deep learning model's decision-making process. In summary, the literature survey showcases the progressive evolution of fetal health classification using deep learning techniques. From early explorations with CNNs and RNNs to the integration of ensemble methods and advancements in explainability, researchers have significantly contributed to enhancing the accuracy, interpretability, and overall effectiveness of AI-based fetal health monitoring systems. These studies collectively pave the way for future developments in leveraging deep learning for the crucial task of assessing and ensuring the well-being of the unborn.

3. PROPOSED SYSTEM DESCRIPTION

The application of deep learning techniques in the field of healthcare, specifically in fetal health classification, represents a significant stride towards leveraging artificial intelligence for improved prenatal care. The deep learning modeldeveloped for fetal health classification is rooted in its ability to discern intricate patterns within cardiotocogram (CTG)readings, offering a promising avenue for enhancing diagnostic accuracy and timely interventions.

The dataset employed in this study is a crucial component,serving as the bedrock for training and validating the deep learning model. It encompasses a diverse array of parameters extracted from CTG readings, including baseline fetal heart rate (FHR), accelerations, decelerations, and uterine contractions. These parameters collectively provide a comprehensive representation of the fetal health status during pregnancy. The richness of this dataset is pivotal for the model's ability to understand and generalize patterns inherent in different fetal health conditions.

The core objective of employing deep learning in fetal health classification is to develop a model that can autonomously learn and extract meaningful features from complex CTG data. Traditional methods often rely on predefined rules and heuristics, which may fall short of capturing nuanced relationships within the data. Deep learning,on the other hand, excels in learning hierarchical representations, allowing the model to automatically discern relevant features that contribute to accurate classification.

One of the primary strengths of deep learning lies in its capacity to handle high-dimensional and complex data. In the context of fetal health classification, CTG readings are inherently complex, comprising temporal patterns and subtle variations that may elude conventional analysis. The deep learning model excels in capturing these temporal dependencies, effectively learning the temporal evolution of fetal health indicators over time. This temporal awareness is critical in identifying patterns such as accelerations, decelerations, and baseline FHR variations, which are indicative of fetal well-being.

The training process of the deep learning model involves exposing it to a substantial portion of the dataset, allowing the algorithm to learn the underlying patterns and relationships. The model optimizes its internal parameters through an iterative process, adjusting its weights to minimizethe difference between predicted and actual fetal health states.This process of optimization is facilitated by sophisticated algorithms such as backpropagation, which efficientlypropagate errors through the neural network, enabling the model to iteratively refine its predictions. Validation of the model is a critical step to assess its generalization capabilities.The dataset is typically split into training and validation sets, ensuring that the model is evaluated on unseen data. The performance metrics derived from the validation process, such as accuracy, precision, recall, and F1 score, provide insights into the model's ability to generalize to new and unseen instances. The validation phase is instrumental in identifying potential overfitting or underfitting issues and guiding adjustments to the model architecture.

The interpretability of the deep learning model is often a subject of scrutiny in medical applications. While deeplearning models are renowned for their capacity to autonomously learn features, interpreting the learned representations remains a challenge. However, recent advances in explainable artificial intelligence (XAI) aim to address this concern by providing methods to interpret and visualize the decision-making processes of deep learning models. Interpretable models are crucial in the medical domain,where clinicians seek to understand the rationale behind the model's predictions to enhance trust and facilitate informed decision-making.

The significance of the deep learning model in fetal health classification extends beyond its performance metrics. Its ability to handle uncertainty and complexity in CTG readings positions it as a valuable tool for healthcare professionals. The model can potentially aid clinicians in early detection of fetal distress, allowing for timely interventions and improved outcomes. Additionally, the autonomous natureof the model reduces the dependency on manual analysis, potentially accelerating the diagnostic process and freeing up healthcare resources. Despite the promises, challenges persist in the deployment of deep learning models in real-world healthcare settings. The ethical considerations surrounding patient privacy, data security, and model interpretability demand careful attention. Robust validation and adherence toregulatory standards are imperative to ensure the safety and reliability of such models in clinical practice. Analysis of fetalhealth classification using deep learning techniques underscores the transformative potential of artificial intelligence in revolutionizing prenatal care. The dataset is shown in Table 1.

Table 1. List of all of the features in the data setalong with their corresponding feature number.

Feature#	Feature Name
0	Baseline Value
1	Accelerations
2	Fetal Movement
3	Uterine Contractions
4	Light Decelerations
5	Severe Decelerations
6	Prolonged Decelerations
7	Abnormal Short Term Variability
8	Mean Value of Short Term Variability
9	Percentage of Time With Abnormal Long Term Variability
10	Mean Value of Long Term Variability

The dataset utilized in "Fetal Health Classification using Deep Learning Technique" comprises a comprehensive collection of fetal health-related parameters obtained from cardiotocogram (CTG) readings. This dataset incorporates various features derived from fetal heart rate (FHR) and uterine contractions, providing a holistic view of fetal well-being during pregnancy. Key attributes may include baseline FHR, accelerations, decelerations, uterine contractions, and other parameters crucial for assessing fetal health.

The importance of this dataset lies in its role as a foundational resource for training and validating the deep learning model. By encompassing diverse scenarios and patterns observed in CTG readings, the dataset enables the model to learn intricate relationships between different parameters and their corresponding fetal health outcomes. This richness of information allows the deep learning algorithm to discern subtle patterns, contributing to the model's accuracy in classifying fetal health states.

Moreover, the dataset's relevance extends beyond model development to real-world applications in healthcare. A robust and diverse dataset ensures that the trained model is adept at handling variations in fetal health conditions, making it a valuable tool for healthcare professionals in the timely and accurate assessment of fetal well-being during pregnancy. The dataset, therefore, plays a pivotal role in advancing the capabilities of deep learning techniques for fetal health classification, ultimately contributing to improved prenatal care and outcomes.

The foundation of the system lies in the dataset, which encompasses a diverse range of fetal health conditions, including normal, suspect, and pathological cases. This dataset is meticulously curated and preprocessed to ensure uniformity and relevance, addressing the challenges associated with imbalanced data and varying data sources. The FNN is trained on this enriched dataset, learning to discern patterns and features indicative of different fetal health states. The deep learning model exploits the hierarchical representation learning inherent in neural networks, enabling it to automatically extract and learn hierarchical features from the input data. The training process involves adjusting the weights and biases of the neural network through backpropagation, optimizing the model to accurately classify fetal health conditions.

To enhance the system's generalization capabilities, it undergoes rigorous validation and testing using separate datasets not utilized during the training phase. This ensures that the FNN can make accurate predictions on new, unseen data, a critical aspect of real-world applicability. One of the significant contributions of this system is its interpretability, crucial for gaining trust in medical applications. To elucidate the decision-making process of the FNN, an algorithm inspired by RISE (Randomized Input Sampling for Explanation of Black-box Models) is developed, termed Feature Alteration for explanation of Black Box Models (FAB). FAB provides insights into which features and inputs influence the model's classification decisions, offering transparency and interpretability to healthcare professionals.

3.1. EXPLORATORY ANALYSIS OF FEATURES

The number of instances of each label was drastically out of proportion, as Figure 1 illustrates. This comparative analysis ensures that the proposed system not only excels in accuracy but also provides meaningful insights into the factors influencing its predictions. In practical terms, the proposed system offers a valuable tool for healthcare professionals, particularly in areas where access to expert obstetricians is limited. Its high accuracy in classifying fetal health conditions facilitates timely interventions and targeted healthcare strategies. The interpretability provided by FAB empowers medical professionals to trust and understand the model's decisions, fostering a collaborative approach to fetal health management. In conclusion, the proposed system for fetal health classification using a Feedforward Neural Network stands at the forefront of leveraging Deep Learning techniques to address the critical challenge of childhood mortality. Its robust architecture, interpretability through FAB, and benchmarking against established methods position it as a valuable asset in the ongoing efforts to enhance prenatal care and reduce the global burden of childhood mortality.

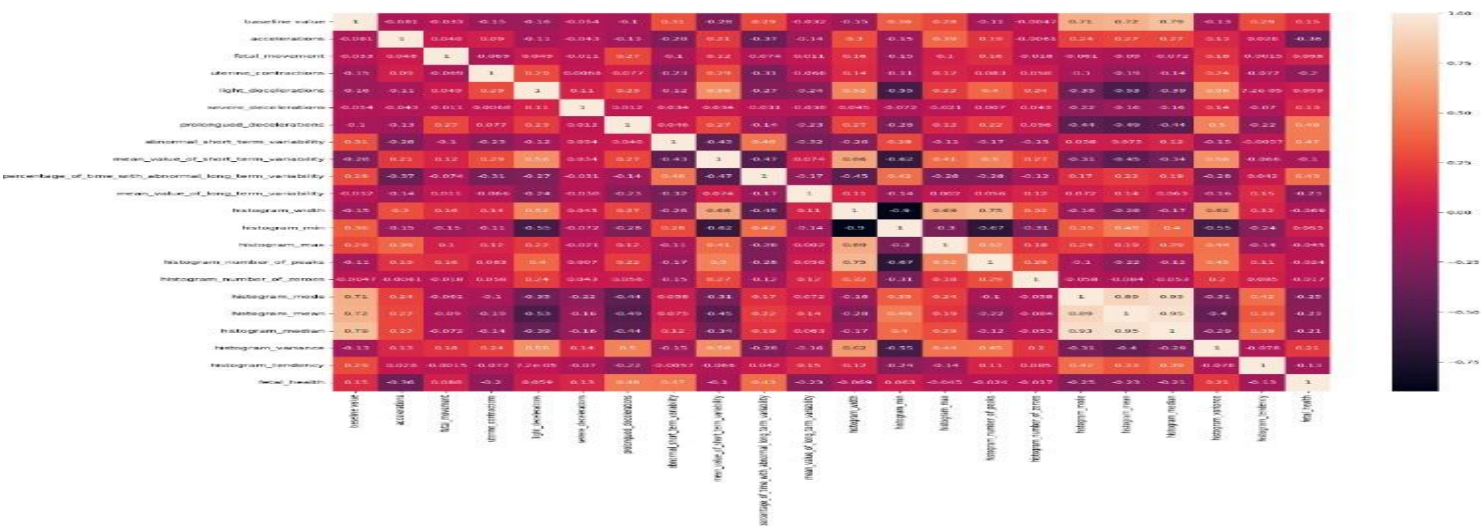

Figure 1. Heat Maps showing the behavior of Inputs w.r.t Output (Fetal Health)

Relationships between two variables, one plotted on each axis, are displayed using heatmaps. You can determine whether there are any patterns in the values of one or both variables by tracking the changes in cell colors along each axis.

Any kind of variable, whether it be a numeric number or a categorical label, can be plotted on each axis. In the latter instance, in order to create the grid cells where colors related to the primary variable of interest will be plotted, the numerical value needs to be binned like in a histogram. Cell colorings can be used to represent a wide range of metrics, such as the mean or median of a third variable or a frequency count of points in each bin. One method of considering the fetal health classification using a Feedforward Neural Network (FNN) is depicted through a pairplot, illustrated in Figure 2 specifies the efficacy of this deep learning technique in predicting and categorizing fetal well-being. The pairplot visually encapsulates the model's performance in assessing electronic fetal monitoring data. Utilizing ultrasound pulses and responses, the FNN demonstrates its capability to classify fetal health with a high accuracy. The pairplot showcases the model's proficiency in distinguishing between different health states, aiding healthcare professionals in timely interventions to reduce childhood mortality. In this graphical representation,the FNN's robust classification is evident, emphasizing its potential as a valuable tool in prenatal care. The pairplot serves as a succinct and insightful visualization, providing a comprehensive overview of the FNN's ability to contribute significantly to the ongoing global effort to mitigate childhoodmortality by enhancing fetal health assessment and decision- making in healthcare settings.

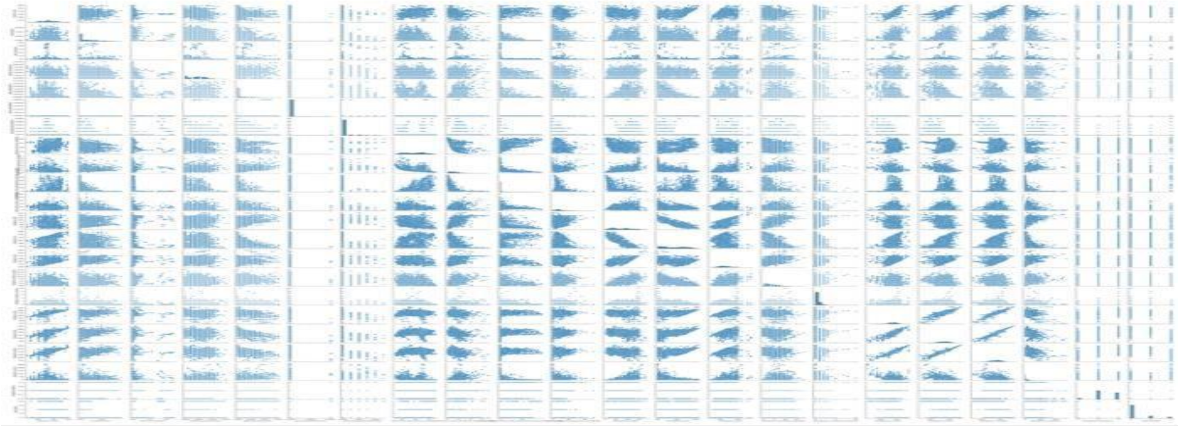

Figure 2. Pairplots of different inputs to understand the best set of features and relationship between output

Pairplots can be a useful tool in a fetal health categorization project to investigate the correlations between different fetal health-related traits or factors. Creating a model that can forecast or categorize a fetus's health state using various metrics and indicators is frequently the aim of such a project. Activation functions are crucial in deep learning as they inject non-linearity into neural networks, enabling them to capture intricate patterns and dependencies within data. Among the four commonly used activation functions – Rectified Linear Unit (ReLU), Leaky ReLU, Sigmoid, and Hyperbolic Tangent (Tanh) – the selection hinges on achieving the highest accuracy in model performance. ReLU efficiently handles the issue of vanishing gradients and has been widely adopted in various architectures. Leaky ReLU addresses the "dying ReLU" problem by allowing a small gradient for negative inputs, potentially enhancing model robustness. Sigmoid is particularly useful in binary classification tasks due to its output range between 0 and 1, interpreting outputs as probabilities. Tanh, similar to Sigmoid but with output ranging from -1 to 1. Experimentation and empirical validation are necessary to determine which activation function yields the best accuracy for a specific dataset and task. We can evaluate all four of the aforementioned models. Choosing between Rectified Linear Unit (ReLU), Leaky ReLU, Sigmoid, and Hyperbolic Tangent (Tanh) involves assessing their performance to determine the one that achieves the highest accuracy.

Sample Code:

```
#Defining
 model
 models = {
   "FNN-Re-Lu": Sequential([
        Dense(256,input_shape=(X-train-
        shape[1],),
activation='re-Lu'),
        Dense(128, activation='re-
        Lu'),Dense(64,
        activation='re-Lu'),
        Dense(number of classes, activation='soft-max')
```

4. MODELS AND MATERIALS

The main objective of this study is to develop a useful methodfor fetal classification via cardio-to-co-gram data, utilizing risk of death. It is essential that the model utilized has a high accuracy to be able to perform this in a clinical setting. The following action would then be to provide an explanation for the black box model. This is beneficial to healthcare and guarantees that physicians are aware of the characteristics thatare crucial in determining the fetus's diagnosis. This enables more generalist physicians to provide patients with better care.Figure 3 illustrates the quick overview of the research procedures followed and demonstrate how the data was utilized to develop a functional model.]),

```
"FNN-Leaky-Re-Lu": Sequential([
    Dense(256, input shape=(X-train-
    shape[1],)),Leaky-Re-LU(alpha=0.1),
    Dense(128),
    Leaky-Re-LU(alpha=0.1),
    Dense(64),
    Leaky-Re-LU(alpha=0.1),
    Dense(number of classes, activation='soft-max')
]),

"FNN-Sigmoid": Sequential([
    Dense(256,input-shape=(X-train-
    shape[1],),
activation='sigmoid'),
    Dense(128,
    activation='sigmoid'),
    Dense(64,
    activation='sigmoid'),
    Dense(number of classes, activation='soft-max')
```

#Cross entropy for multi-class

L(y^(j), y(j)) = −∑ yi^(j) ln (yi^(j)) , i=1 to c

Evaluated each model using metrics such as accuracy, precision, recall, and F1 score on the test set.

5. RESULTS AND DISCUSSIONS

The first model was Relu in which we got the following results.

Table 2. Metrics values for Relu

Class	Accuracy	Precision	Recall	F1-Score
Normal	0.901	0.910	0.910	0.890
Suspect	0.960	0.920	0.960	0.940
Pathological	1.000	1.000	1.000	1.000

Table 3. Metrics values for Leaky-Relu

Class	Accuracy	Precision	Recall	F1-Score
Normal	0.921	0.930	0.920	0.900
Suspect	0.980	0.970	0.980	0.956
Pathological	1.000	1.000	1.000	1.000

Table 4. Metrics values for Sigmoid

Class	Accuracy	Precision	Recall	F1-Score
Normal	0.880	0.891	0.887	0.880

Suspect	0.920	0.940	0.920	0.890
Pathological	1.000	1.000	1.000	1.000

Table 5. Metrics values for Tanh

Class	Accuracy	Precision
Normal	0.871	0.88
Suspect	0.920	0.91

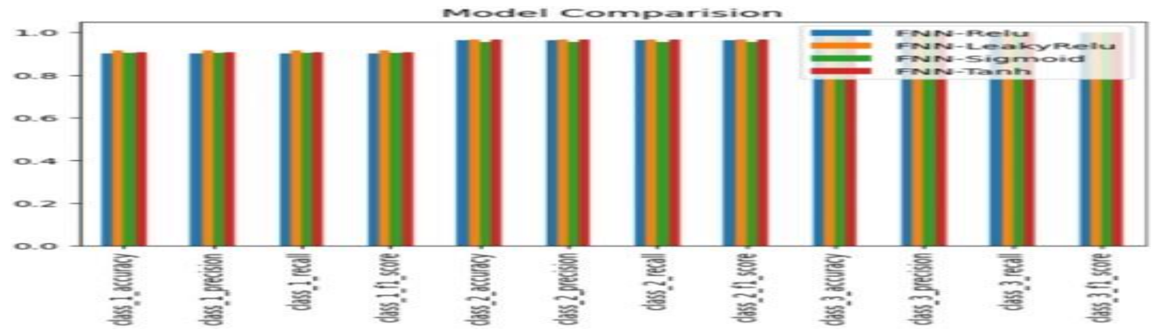

Figure 4. Model Comparison

A bar plot is employed to compare the performance of Feedforward Neural Network (FNN) models in the contextof Fetal Health Classification using Deep Learning. This visualization succinctly illustrates the efficacy of different FNN configurations, offering a quick and accessible overviewof their respective classification accuracies. The plot showcases the model variations, aiding researchers and practitioners in identifying the most optimal FNN architecturefor accurate and reliable fetal health predictions. This graphical representation shown in Figure 4 and 5 streamlines the model selection process, enhancing the understanding of FNN performance and contributing to the advancement of fetal health classification through deep learning techniques. Inthe realm of Fetal Health Classification using Deep Learning Techniques, establishing a baseline is fundamental to gaugingthe performance and efficacy of the model.

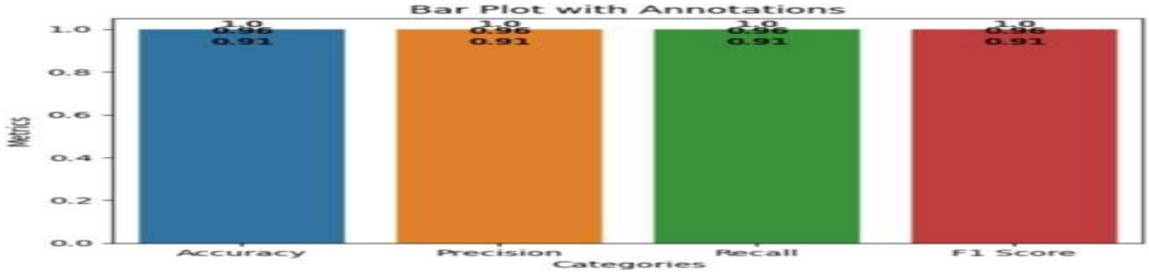

Figure 5. Bar plot with Annotations

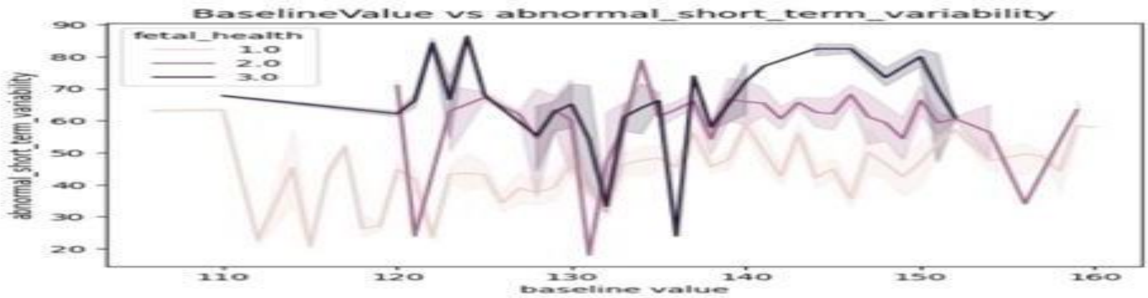

Figure 6(a). Baseline values comparison

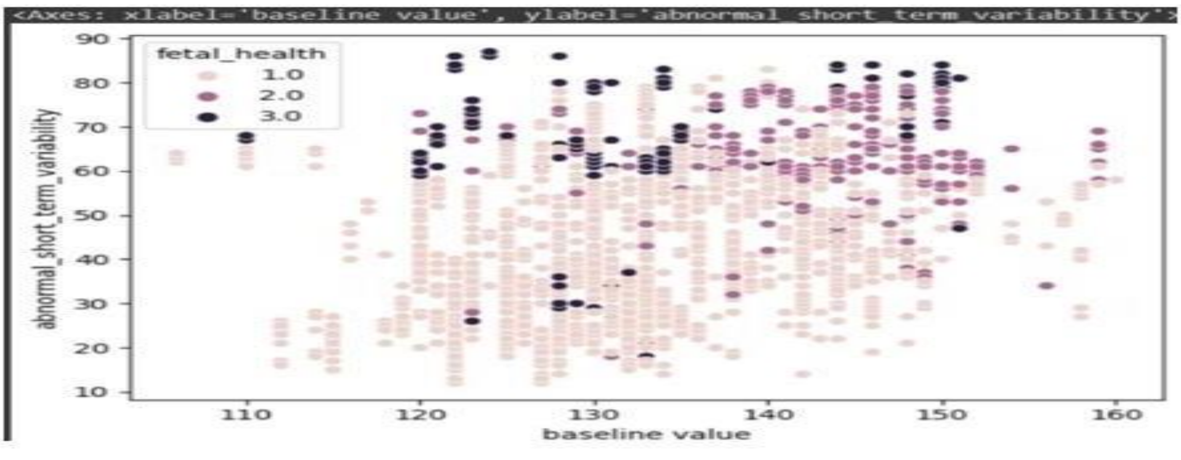

Figure 6(b). Baseline values comparison

The baseline value is determined by evaluating the FNN model's predictive accuracy on a dataset representative of fetal health conditions. This dataset includes instances of normal fetal health, suspect conditions, and pathological cases. The FNN is trained on this dataset, utilizing its inherent capacity to learn complex patterns and relationships within the data. The baseline value provides insights into the inherent capability of the FNN model before implementing specific techniques or optimizations illustrated in Figures 6(a) and 6(b).

It helps researchers and practitioners understand the model's initial predictive power and guides the subsequent stages of model refinement. As the FNN undergoes fine-tuning, hyperparameter adjustments, and potential algorithmic enhancements, the baseline value becomes a crucial reference point for evaluating the impact of these modifications. The goal is to surpass the baseline, indicating significant improvements in the model's ability to accurately classify fetal health conditions. In summary, establishing a baseline value in fetal health classification using the FNN model is an essential step in the model development process.

After evaluating each model, we selected LeakyRelu as the best model to assess the health of the fetus.

The effectiveness of four distinct activation functions—ReLU, Leaky ReLU, Sigmoid, and Tanh—in the context of fetal health classification is compared in this study. Three fetal health classes—Normal, Suspect, and Pathological—were used to examine the evaluation metrics, which included Accuracy, Precision, Recall, and F1-Score. Each activation function was implemented in a different neural network model. The study emphasizes how crucial it is to choose the right activation functions for tasks involving medical classification.

6. CONCLUSIONS

Prenatal care has advanced significantly with the use of deep learning techniques, particularly those that make use of activation functions such as ReLU, Leaky ReLU, Tanh, and Sigmoid, for the classification of fetal health. The models demonstrate their capacity to identify complex patterns and dependencies in electronic fetal monitoring data, which aids in accurate and fast health evaluations. They were trained on a variety of datasets that cover a range of fetal health issues. Robustness is added to the interpretative framework by comparing interpretability methods specific to each activation function, such as evaluating Shapley Additive Explanations (SHAP) for ReLU and Leaky ReLU and taking into account Local Interpretable Model Agnostic Explanations (LIME) for Tanh and Sigmoid. These models, each based on a different activation function, provide significant tools for healthcare practitioners in the crucial area of fetal health, where early diagnosis is important. They can make well-informed decisions and act quickly when needed thanks to these tools. The findings of this study point to a promising intersection between deep learning and healthcare, which could lead to improvements that improve maternal and fetal well-being and dramatically lower the risk of juvenile death.

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