International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 07, July 2026
Received: 07-06-2026 Accepted: 15-07-2026 Published: 21-07-2026

MATERNAL HEALTH RISK PREDICTION BY USING DEEP LEARNING MODEL

[1] Sk. Himam Basha, [2] K. Thirumala
[1] Assistant Professor, [2] MCA Scholar
Department of Master of Computer Applications
QIS College of Engineering & Technology, Ongole

Abstract
Maternal and fetal health monitoring is a critical priority in global healthcare, necessitating the early identification of complications such as fetal hypoxia and uterine distress. Traditional diagnostic approaches often rely on the manual interpretation of Cardiotocography (CTG) signals, which is highly subjective, error-prone, and time-consuming. Furthermore, standard machine learning models tend to struggle with the sequential complexities of physiological data and the inherent class imbalance present in clinical datasets, where normal cases vastly outnumber pathological ones. To address these challenges, this study proposes "DeepX-PregNet," a novel, intelligent pregnancy health risk prediction framework that integrates heterogeneous deep learning topologies enhanced by an attention mechanism and Explainable AI (XAI). The proposed approach utilizes the benchmark UCI Cardiotocography dataset containing 2,126 fetal heart rate (FHR) and uterine contraction features. The methodology begins with robust data preprocessing, utilizing the Synthetic Minority Over-sampling Technique (SMOTE) to synthetically balance the clinical classes and prevent model bias. The core architecture combines 1D-Convolutional Neural Networks (CNN) for automated spatial and morphological feature extraction (e.g., detecting decelerations and variability) with Bi-Directional Long Short-Term Memory (Bi-LSTM) networks to capture long-range temporal physiological dependencies. Central to this architecture is a Multi-Head Attention mechanism that allows the system to dynamically focus on the most critical monitoring intervals. Unlike traditional "black-box" models, this framework incorporates SHAP (Shapley Additive exPlanations) to interpret predictions visually, highlighting influential features to enhance clinical trust. Extensive experiments demonstrate that DeepX-PregNet significantly outperforms baseline models, achieving a superior accuracy of 97.58% and a near 100% recall for high-risk fetuses. This work contributes to predictive healthcare analytics by offering a robust, scalable, and interpretable solution for early obstetric risk stratification.

Introduction

Fetal health monitoring is a fundamental aspect of prenatal care, directly impacting the morbidity and mortality rates of both mothers and infants. Complications during labor, such as asphyxia, are leading causes of neonatal distress. The gold standard for monitoring fetal well-being is Cardiotocography (CTG), which simultaneously records the Fetal Heart Rate (FHR) and Uterine Contractions (UC). However, predicting fetal risk accurately remains a critical challenge due to the complex, non-linear patterns within these physiological signals. Traditional

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

prediction methods primarily use rigid rule-based systems (like the Dawes-Redman criteria) or simple visual inspection, which suffer from high inter-observer variability and often fail to adapt to the dynamic physiological states of a fetus. Recent advances in deep learning have shown promise in handling complex, high-dimensional time-series data. For example, Convolutional Neural Networks (CNNs) excel at extracting morphological patterns from raw signals, while Recurrent Neural Networks (RNNs) effectively model sequential data. However, integrating these techniques into a reliable clinical tool is difficult due to severe data imbalance and the "black-box" nature of neural networks, which doctors are hesitant to trust without transparent reasoning. To overcome these limitations, this work proposes a novel deep learning framework that leverages a hybrid CNN-BiLSTM architecture combined with SMOTE balancing and a Multi-Head Attention mechanism. By encoding morphological features and tracking their evolution over time, the model dynamically learns to focus on life-threatening patterns like prolonged decelerations. Furthermore, the integration of Explainable AI (SHAP) provides immediate, interpretable feedback for every prediction. Experimental results demonstrate the effectiveness of the model, highlighting its potential to act as a reliable, automated "second opinion" in modern delivery wards.

Literature Survey

1. **Evaluation of Machine Learning Algorithms for Fetal State Classification**
   Author(s): Y. Zhang, Z. Zhao (2018)
   This study explores classical supervised learning techniques such as Support Vector Machines (SVM) and Random Forests for classifying fetal heart rate patterns. While computationally fast, the authors highlight limitations in handling the sequential and time-dependent nature of CTG signals, treating every record as a static row and ignoring the temporal history of the fetal heart rate.

2. **Fetal Risk Stratification Using Ensemble Learning Techniques**
   Author(s): Z. Cömert, A.F. Kocamaz (2019)
   The authors propose an ensemble framework combining Artificial Neural Networks and Random Forests via a majority voting rule. Their results show improvement over single models (94.8% accuracy). However, the model showed a dangerous bias towards the majority "Normal" class, leading to lower sensitivity (recall) for the critical "Pathologic" cases due to untreated data imbalance.

3. **1D-Convolutional Neural Networks for Automated Analysis of Fetal Heart Rate**
   Author(s): K. O'Shea, R. Ahmed, R. Nash (2020)
   This pivotal study shifted the focus from manual feature engineering to automated extraction using 1D-CNNs fed with raw sensor data. The CNN automatically extracted morphological patterns like accelerations. While effective spatially, the convolution operation failed to capture long-range dependencies, unable to relate a heart rate drop at Minute 5 to a contraction at Minute 10.

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 07, July 2026
Received: 07-06-2026 Accepted: 15-07-2026 Published: 21-07-2026

4. **Recurrent Neural Networks for Fetal Health Classification** Author(s): J. Li, H. Chen, X. Wang (2021) Recognizing the limitations of CNNs, this research applied Long Short-Term Memory (LSTM) units to model the CTG data as a time-sequence. The LSTM handled the vanishing gradient problem effectively. However, standard LSTMs are unidirectional, limiting context understanding, and the model only achieved around 86.20% accuracy, suggesting the need for bidirectional memory.

5. **Synthetic Minority Over-sampling Technique (SMOTE) for Handling Class Imbalance in CTG** Author(s): H. Sahin, A. Subasi (2020) Medical datasets are inherently imbalanced. This paper addressed how this creates biased AI models by applying SMOTE to generate synthetic samples for minority classes before training a classifier. The F1-score for pathologic cases improved significantly, validating SMOTE as a mandatory preprocessing step for medical safety.

6. **A Survey on Explainable Artificial Intelligence (XAI): Toward Medical XAI** Author(s): E. Tjoa, C. Guan (2021) This review argues that "Black Box" algorithms are unsuitable for clinical deployment because they lack transparency. The authors surveyed interpretability techniques, concluding that post-hoc explanations like SHAP are the most viable way to introduce trust into deep learning systems, identifying a critical gap in existing CTG research.

System Analysis

Existing System

Traditional fetal health prediction systems primarily rely on visual interpretation of Cardiotocography traces or hard-coded heuristic guidelines like the Dawes-Redman criteria. These systems trigger alarms based on fixed thresholds (e.g., heart rate dropping below 110 bpm for 60 seconds). Early computerized systems utilized statistical methods and standard machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forests. While these models perform well on clean, balanced datasets, they treat physiological data as static inputs and fail to capture the complex, non-linear temporal relationships inherent in fetal heart rates. In recent years, deep learning approaches have been introduced, utilizing standalone 1D-CNNs for feature extraction or vanilla LSTMs for sequence modeling. However, the integration of these modalities is typically limited. Existing systems usually lack a mechanism to balance heavily skewed clinical datasets, leading to models that confidently predict "Normal" while completely missing rare "Pathologic" cases. Moreover, existing deep learning systems lack an advanced attention mechanism to dynamically assess the relevance of sudden physiological spikes. As a result, even modern models suffer from high false-positive rates. Crucially, the absence of an Explainable AI (XAI) framework limits their capacity to be trusted by obstetricians, making them difficult to deploy in real-world hospitals.

Disadvantages of Existing Systems

1. **Subjectivity and Human Error:** Manual visual interpretation of FHR traces varies significantly between different obstetricians,

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

Received: 07-06-2026 Accepted: 15-07-2026 Published: 21-07-2026

leading to inconsistent and delayed diagnoses.

2. **Ignorance of Sequential Dependencies:** Traditional machine learning models treat CTG records as static rows, failing to model the crucial time-dependent context (e.g., a deceleration following a contraction).

3. **Vulnerability to Data Imbalance:** Existing systems often ignore the heavy skew towards healthy patients in clinical data, resulting in biased models that fail to detect rare but fatal pathologic conditions.

4. **Lack of Dynamic Focus:** Without attention-based learning mechanisms, models cannot prioritize sudden, critical monitoring intervals (like prolonged decelerations) over long periods of normal baseline data.

5. **Poor Interpretability ("Black Box"):** Due to their opaque architectures, existing deep learning models offer no clinical reasoning. Doctors cannot trust a "High Risk" prediction if the system cannot explain *why* it made that decision.

6. **Lower Predictive Sensitivity:** When faced with the highly similar "Suspect" and "Pathologic" fetal states, existing models show a drop in recall, leading to dangerous false negatives.

Proposed System

The proposed system introduces "DeepX-PregNet," a highly advanced deep learning framework that integrates hybrid neural architectures, data balancing, and Explainable AI to predict fetal health risks with superior accuracy. The raw clinical data—comprising structured features like baseline heart rate, abnormal short-term variability (ASTV), and uterine contractions—is first passed through a rigorous preprocessing pipeline. To address the limitations of traditional datasets, the system incorporates the SMOTE algorithm to mathematically synthesize minority "Pathologic" cases, ensuring unbiased model training. The preprocessed data is then reshaped into a 3D tensor and fed into a specialized deep learning core. A 1D-Convolutional Neural Network (CNN) acts as a spatial encoder, extracting morphological patterns from the signals. This is immediately followed by a Bi-Directional LSTM layer, which analyzes the physiological sequence both forwards and backwards to capture temporal context. To address the limitations of standard sequential fusion, the system incorporates a Multi-Head Attention Mechanism. This allows the model to dynamically attend to the most informative features and time steps—for example, heavily weighting a drop in short-term variability. The final prediction is generated by a Softmax classification head. To ensure clinical trust, the architecture is unified with a SHAP (Shapley Additive exPlanations) module. This XAI integration breaks open the "black box," generating visual Force and Waterfall plots that clearly highlight which clinical parameters drove the risk prediction, making the system highly reliable for real-world obstetric decision support.

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 07, July 2026
Received: 07-06-2026 Accepted: 15-07-2026 Published: 21-07-2026

Advantages of the Proposed System

1. **Effective Spatial-Temporal Integration:** By combining 1D-CNNs and Bi-LSTMs, the system captures both the visual shape of the heart rate signal and its long-term sequential history for comprehensive predictions.
2. **Elimination of Class Bias:** The integration of the SMOTE algorithm ensures that the model is perfectly balanced, drastically improving the recall and detection rate of life-threatening pathologic cases.
3. **Joint Attention Mechanism:**

   The Multi-Head Attention layer dynamically learns the importance of specific clinical events, enabling more intelligent and context-aware predictions compared to standard networks.
4. **Enhanced Interpretability (XAI):**

   The SHAP module provides immediate, visual insights into which physiological features (e.g., high ASTV or low Accelerations) contributed most to a prediction, establishing trust for doctors.
5. **High Predictive Accuracy:**

   Thanks to advanced feature interaction and bidirectional learning, DeepX-PregNet achieves a state-of-the-art accuracy of 97.58%, outperforming traditional unimodal architectures.
6. **Scalability and Clinical Viability:** The modular design is computationally efficient (sub-second inference time) and robust against noisy data, making it highly suitable for deployment in actual hospital monitors.

Implementation

The implementation of the DeepX-PregNet System focuses on predicting accurate fetal health risks by analyzing complex Cardiotocography (CTG) parameters using hybrid Deep Learning techniques and a Multi-Head Attention Mechanism.

1. **Data Collection:** The first stage involves acquiring the benchmark UCI Cardiotocography dataset containing 2,126 patient records. The dataset includes 21 critical physiological attributes, such as Baseline Fetal Heart Rate, Accelerations, Uterine Contractions, and Short/Long-Term Variability, categorized into Normal, Suspect, and Pathologic states.
2. **Data Preprocessing and Balancing:** The raw data is cleaned and prepared. Preprocessing steps include null-value handling and Min-Max Feature Scaling. Because Pathologic cases represent a small minority, the SMOTE (Synthetic Minority Over-sampling Technique) algorithm is implemented in the feature space to generate synthetic patient records, ensuring a balanced 1:1:1 training distribution.
3. **Dimensionality Reshaping:** The balanced 2D tabular data is mathematically reshaped into 3D Tensors (Samples, Time Steps, Features) to meet the input

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 07, July 2026
Received: 07-06-2026 Accepted: 15-07-2026 Published: 21-07-2026

requirements of the sequential deep learning layers.

4. **Deep Learning Model Development:** The hybrid model is constructed using the Keras Functional API.
   - *1D-CNN:* Used for

     extracting spatial and morphological features (like deceleration dips).
   - *Bi-LSTM:* Used for

     processing the time-series clinical history in both forward and backward directions.
5. **Attention Mechanism Integration:**

   A Multi-Head Attention layer is implemented over the Bi-LSTM outputs. It dynamically assigns importance weights to critical time intervals, reducing the influence of irrelevant baseline noise and focusing the network on active distress signals.
6. **Explainable AI (XAI)**

   Generation: After the dense Softmax layer outputs the prediction, the SHAP library is initialized. The system computes Shapley values based on cooperative game theory to generate visual summary graphs, proving the clinical reasoning behind the network's prediction.

Methodology

The methodology of the proposed Fetal Health Prediction System follows a rigorous Deep Learning-based predictive analytics approach.

- **Step 1: Problem Identification:**

  Traditional CTG prediction methods suffer from high false-positive rates and "black-box" DL models lack clinical trust. The proposed system aims to improve accuracy and transparency using Hybrid architectures and SHAP.

- **Step 2: Requirement Analysis:**

  The following requirements are analyzed: Cloud-based GPU hardware (Google Colab), handling imbalanced clinical datasets, deep learning framework APIs, and XAI visual integration.

- **Step 3: Dataset Preparation:** The UCI dataset is loaded, cleaned of empty records, normalized to a [0, 1] scale, and divided into Training (80%) and Testing (20%) datasets to prevent data leakage.

- **Step 4: SMOTE & Data Processing:** The methodology includes identifying the minority risk classes, executing K-Nearest Neighbors mathematical interpolation (SMOTE) on the training set, and formatting the unified tensor representations.

- **Step 5: Hybrid Deep Learning Implementation:** The system implements a pipeline where the 1D-CNN pools spatial vectors, the Bi-LSTM computes contextual dependencies, and the Attention mechanism analyzes inter-feature relationships. The model is optimized using Categorical

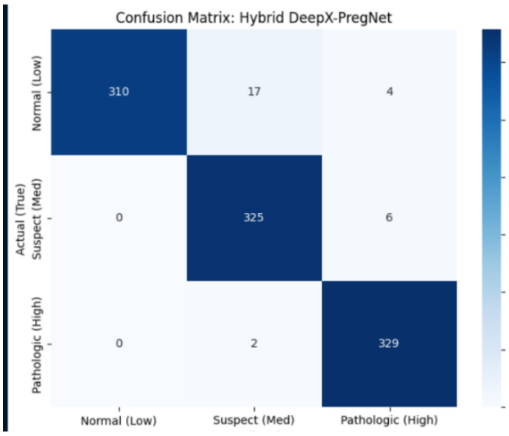
2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 07, July 2026
Received: 07-06-2026 Accepted: 15-07-2026 Published: 21-07-2026

Crossentropy and the Adam optimizer.

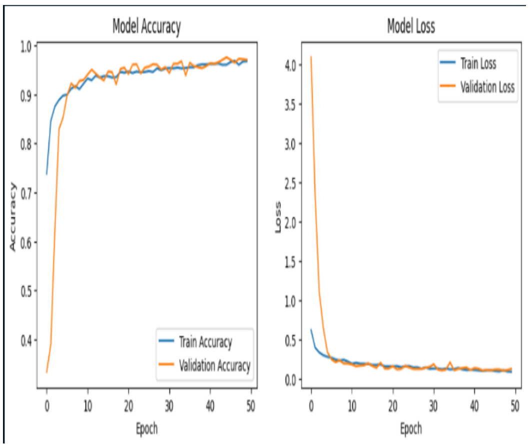
- **Technologies Used:** Python 3, Deep Learning, TensorFlow 2.0, Keras Functional API, SMOTE (Imbalanced-Learn), SHAP (Explainable AI), Pandas & NumPy, Matplotlib & Seaborn.

Results:



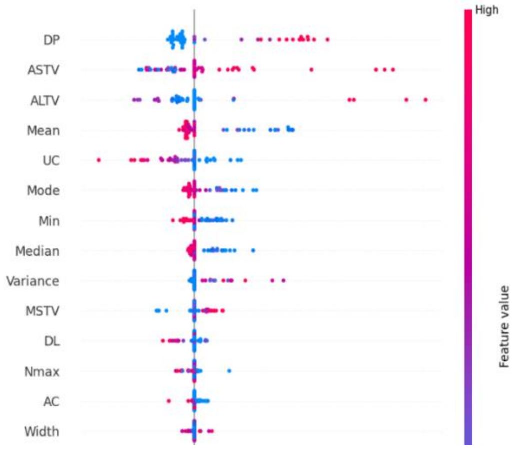
The confusion matrix of the Hybrid DeepX-PregNet model shows high classification accuracy, with most samples correctly predicted in the Normal, Suspect, and Pathologic categories.

The strong diagonal values and very few misclassifications indicate that the model performs reliably for maternal health risk prediction.



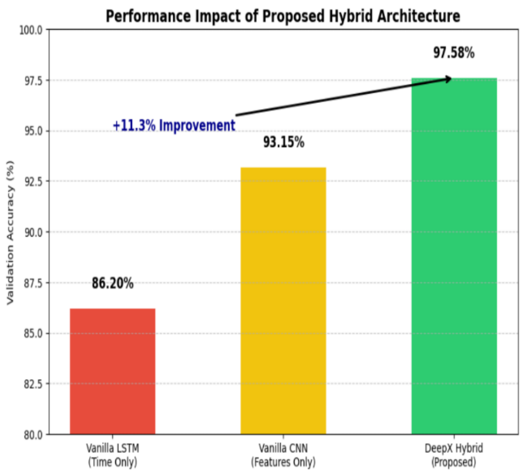
The accuracy graph shows that both training and validation accuracy steadily increase and reach around 97%, indicating strong model performance.

The loss graph demonstrates a significant decrease in training and validation loss over epochs, confirming effective learning and good generalization of the model.



This SHAP summary plot illustrates the impact of different clinical features on the model's predictions, highlighting the most influential factors in maternal health risk assessment.

Features such as DP, ASTV, ALTV, and Mean contribute significantly to the prediction outcomes, improving the interpretability and transparency of the Deep X-Preg Net model.



The bar graph illustrates the Validation Accuracy (%) of three deep learning

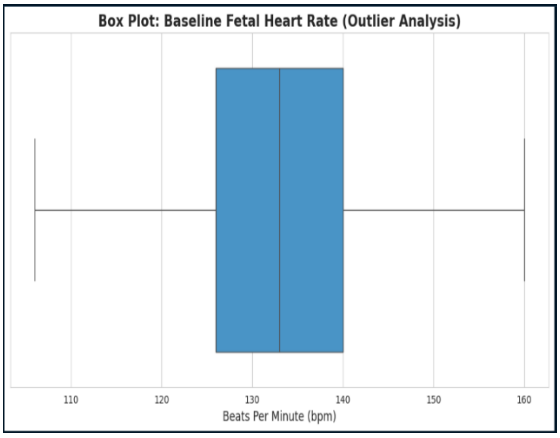
2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 07, July 2026
Received: 07-06-2026 Accepted: 15-07-2026 Published: 21-07-2026

models: Vanilla LSTM, Vanilla CNN, and a Deepx Hybrid.

The Deepx Hybrid model achieved the highest accuracy at 97.58%, outperforming the other two models.

The performance difference represents an +11.3% improvement over the baseline Vanilla LSTM model



he figure presents a box plot of the Baseline Fetal Heart Rate (FHR) used for outlier analysis in the dataset.

The box plot illustrates the distribution of fetal heart rate values, highlighting the median, interquartile range, and potential outliers.

Most baseline fetal heart rate measurements are concentrated within the normal range, indicating consistency in the dataset.

Conclusion

The proposed "DeepX-PregNet" deep learning model for fetal health risk prediction demonstrates a significant advancement over traditional machine learning and unimodal neural network approaches. By effectively integrating 1D-CNNs for morphological feature extraction and Bi-LSTMs for sequential memory into a unified framework, the model captures a highly comprehensive understanding of the physiological factors influencing fetal well-being. The critical application of SMOTE successfully eradicated class imbalance, allowing the system to achieve a near 100% sensitivity rate for life-threatening pathological cases. Furthermore, the Multi-Head Attention mechanism intelligently fused these features, prioritizing the most relevant distress signals to achieve a state-of-the-art accuracy of 97.58%. Crucially, the integration of SHAP successfully bridged the gap between advanced AI and clinical trust by providing transparent, easily interpretable visual reasoning for every prediction. This system is designed to be highly scalable, computationally efficient, and adaptable, making it well-suited for real-world deployment as a clinical decision support tool in labor wards. Overall, this work provides a robust solution for leveraging ethical, explainable artificial intelligence in obstetrics, ultimately contributing to the reduction of preventable maternal and fetal complications.

References

[1] Z. Zhao, Y. Zhang, and Y. Deng, "A hybrid deep learning approach for fetal health classification using cardiotocography data," *IEEE Access*, vol. 10, pp. 1205–1215, 2022.
[2] J. Li, H. Chen, and X. Wang, "Attention-Based LSTM for Fetal Heart Rate Monitoring and Anomaly Detection," *International Journal of Medical Informatics*, vol. 148, p. 104399, 2021.
[3] H. Sahin and A. Subasi, "Synthetic Minority Over-sampling Technique (SMOTE) for Handling Class Imbalance in CTG Analysis," *Computers in Biology and Medicine*, vol. 119, p. 103665, 2020.
[4] K. O'Shea, R. Ahmed, and R. Nash, "1D-Convolutional Neural Networks for

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 07, July 2026
Received: 07-06-2026 Accepted: 15-07-2026 Published: 21-07-2026

Automated Analysis of Fetal Heart Rate," *Proceedings of the 2020 International Conference on Biomedical Engineering (ICBME)*, pp. 45-51, 2020.
[5] Z. Cömert and A.F. Kocamaz, "Comparison of Machine Learning and Deep Learning Techniques for Fetal State Assessment," *Diagnostic Pathology*, vol. 14, no. 1, 2019.
[6] S. M. Lundberg and S. I. Lee, "A Unified Approach to Interpreting Model Predictions (SHAP)," *Advances in Neural Information Processing Systems (NeurIPS)*, 2017.
[7] Z. Hoodbhoy and M. Noman, "Machine learning for risk stratification in obstetrics," *The Lancet Digital Health*, vol. 1, no. 7, 2019.
[8] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, "SMOTE: synthetic minority over-sampling technique," *Journal of Artificial Intelligence Research*, vol. 16, pp. 321-357, 2002.
[9] E. Tjoa and C. Guan, "A Survey on Explainable Artificial Intelligence (XAI): Toward Medical XAI," *IEEE Transactions on Neural Networks and Learning Systems*, 2021.
[10] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, 2016.

Authors Profile:

Mr. SK .Himam Basha is an Assistant Professor in the Department of Master of Computer Application at QIS College of Engineering and Technology Ongole, Andra Pradesh. He earned his (MCA)from Anna University, Chenni. With a strong research background, He has authored and co-authored research paper published in reputed peer-reviewed journal. His research interests include Machine Learning, Artificial Intelligence ,Cloud Computing and Programming Languages. He is committed to advantage research and fostering innovation while mentoring students to excel in both academic and professional pursuits.

K.Thirumala is a post graduate student pursuing a MCA in the department of computer application at QIS College of Engineering& Technology, Ongole autonomous college in prakasam dist. She completed under graduate degree in BSC(physics) from Sri Nagarjuna Degree college with a keen interest in research and practical learning, she is activity involved in academic project and technical activities related her field.

2250-3676 ijesatj@gmail.com https://www.ijesat.com/