Heart Disease Classification With Ecg Signals Using Deep Neural Networks

K. Lakshmanrao[1],Y Kotari Harsha Vardhan[2], Koka Kasaiah[3], Nelluri Jaswanth[4], Mitta Ganesh[5]

[2,3,4,5]UG Student,ECE,Chalapathi Institute Of Engineering&Technology Guntur-Andhra Pradesh,India

[1] Professor ECE,Chalapathi Institute Of Engineering&Technology Guntur-Andhra Pradesh,India

***Abstract*—**Heart disease continues to be one of the leading causes of death worldwide, making early detection and continuous monitoring critically important for improving patient outcomes. This paper presents a novel approach for heart disease classification using electrocardiogram (ECG) signals combined with deep neaural network techniques. The proposed system integrate machine learning to provide an efficient and real time diagnostic solution.The system utilizes an ECG sensor to capture the electrical activity of the heart and a MAX30102 sensor to measure heart rate and blood oxygen levels, offering comprehensive physiological insights. An Arduino Uno serves as the central unit for data acquisition and processing, while an LCD module provides real-time feedback to the user. The collected ECG signals are further analyzed using a deep neural network model trained on relevant datasets to accurately classify cardiac conditions into normal and abnormal categories.

Keywords— Electrocardiogram (ECG), Heart Disease Classification, Deep Neural Networks (DNN), Machine Learning, Biomedical Signal Processing, Arduino Uno, MAX30102 Sensor, Real-Time Monitoring, Healthcare Systems, Embedded Systems.

I. INTRODUCTION

Cardiovascular diseases (CVDs) are among the leading causes of mortality worldwide, posing a significant challenge to global healthcare systems. According to recent medical studies, millions of people lose their lives each year due to heart-related conditions such as arrhythmias, myocardial infarction, and other cardiac abnormalities. Early detection and continuous monitoring of heart activity play a crucial role in reducing mortality rates and improving patient outcomes. However, traditional diagnostic methods are often limited by high costs, bulky equipment, and the need for expert interpretation.

The electrocardiogram (ECG) is one of the most widely used non-invasive tools for monitoring the electrical activity of the heart. It provides valuable information about heart rhythm and helps in identifying abnormalities. Despite its effectiveness, conventional ECG analysis typically relies on manual interpretation by trained cardiologists, which can be time-consuming and prone to human error. Furthermore, most existing systems are confined to clinical environments, making continuous monitoring difficult, especially in rural or resource-limited areas.

With advancements in embedded systems and artificial intelligence, there is a growing opportunity to develop smart and portable healthcare solutions. Deep learning techniques, particularly deep neural networks (DNNs), have shown remarkable performance in analyzing complex biomedical signals such as ECG data. These models are capable of automatically extracting features and identifying hidden patterns, thereby improving the accuracy and efficiency of disease classification compared to traditional machine learning approaches.

In this context, the present work proposes a heart disease classification system using ECG signals and deep neural networks. The system integrates hardware components such as an Arduino Uno, ECG sensor, MAX30102 sensor, LCD display, and a regulated power supply to acquire physiological signals in real time. The ECG sensor captures cardiac electrical activity, while the MAX30102 sensor measures heart rate and blood oxygen saturation (SpO_2), providing additional health parameters for analysis. The collected data is processed and analyzed using a deep neural network model to classify heart conditions as normal or abnormal.

The proposed system aims to provide a cost-effective, portable, and efficient solution for real-time heart health monitoring. By combining embedded hardware with advanced deep learning techniques, the system reduces dependency on specialized medical equipment and expert analysis. This makes it particularly useful for remote healthcare applications and continuous patient monitoring. Ultimately, this work contributes to the development of intelligent healthcare systems that enhance early diagnosis and improve accessibility to medical services.

II. REVIEW LITERATURE SURVEY

Doi:10.48047/ijiee.2026.16.2.14

Recent advancements in artificial intelligence and biomedical signal processing have significantly enhanced the detection and classification of heart diseases using electrocardiogram (ECG) signals. ECG is widely recognized as an effective non-invasive tool for monitoring the electrical activity of the heart and identifying abnormalities such as arrhythmias. With the emergence of deep learning techniques, researchers have increasingly focused on developing automated systems that can analyze ECG signals with high accuracy and minimal human intervention. Deep neural networks, particularly convolutional neural networks (CNNs), have demonstrated superior performance in extracting meaningful features directly from raw ECG data, eliminating the need for manual feature engineering.

Several notable studies have contributed to this domain. Rajpurkar et al. (2017) developed a deep CNN model capable of detecting cardiac arrhythmias with performance comparable to that of experienced cardiologists, highlighting the potential of deep learning in clinical diagnosis. Similarly, Acharya et al. (2017) proposed a CNN-based model for heartbeat classification, achieving high accuracy and demonstrating improved performance over traditional machine learning methods.

Hannun et al. (2019) introduced a deep learning framework for continuous ECG monitoring, capable of detecting multiple cardiac conditions in real time, thereby supporting long-term patient monitoring. Kachuee et al. (2018) further improved model adaptability by proposing a transferable deep learning approach that reduces dependence on large labeled datasets. In addition, Kiranyaz et al. (2016) presented a patient-specific ECG classification system using one-dimensional CNNs, which adapts to individual variations and enhances diagnostic precision. Zihlmann et al. (2017) also demonstrated that deep learning models are robust against noise in ECG signals, making them suitable for real-world healthcare applications.

Despite these advancements, existing systems still face several limitations. Most traditional ECG monitoring systems used in hospitals are expensive, bulky, and require expert interpretation, making them unsuitable for continuous or remote monitoring. Although some portable devices have been developed, they often lack intelligent diagnostic capabilities and rely on basic parameter monitoring rather than automated classification. Earlier approaches based on conventional machine learning techniques require manual feature extraction, which is time-consuming and may not capture complex patterns effectively, leading to reduced accuracy.

Therefore, there is a clear need for a system that integrates deep learning with cost-effective and portable hardware to enable real-time heart disease classification. The proposed system addresses this gap by combining ECG signal acquisition with deep neural network-based analysis using embedded components such as Arduino Uno, ECG sensor, and MAX30102 sensor. This integration enables automatic classification of heart conditions, reduces dependency on expert analysis, and provides a practical solution for continuous health monitoring, especially in resource-limited environments.

III. RESEARCH METHODOLOGY

The proposed research methodology focuses on the design and implementation of an intelligent heart disease classification system using ECG signals and deep neural networks. The methodology is structured into multiple stages, including data acquisition, signal preprocessing, feature learning, model training, and real-time classification. Each stage is carefully designed to ensure accurate and efficient detection of cardiac abnormalities.

Initially, physiological data is acquired using biomedical sensors integrated with embedded hardware. An ECG sensor is used to capture the electrical activity of the heart, while a MAX30102 sensor measures heart rate and blood oxygen saturation (SpO_2), providing additional health indicators. These sensors are interfaced with an Arduino Uno, which acts as the central data acquisition unit. The Arduino processes the raw signals and transmits the data for further analysis, while an LCD module displays real-time readings for user interaction.

Once the data is collected, preprocessing techniques are applied to improve signal quality. ECG signals are often affected by noise such as baseline wander, power line interference, and motion artifacts. To address this, filtering techniques are employed to remove noise and enhance the signal. The cleaned data is then normalized and segmented into smaller samples suitable for model training. This step ensures that the input data is consistent and improves the performance of the deep learning model.

Doi:10.48047/ijiee.2026.16.2.14

The next stage involves feature extraction and model development using deep neural networks. Unlike traditional methods that rely on manual feature extraction, the proposed approach uses a DNN model that automatically learns important features from the ECG signals. The model is trained on labeled datasets containing both normal and abnormal ECG patterns. During training, the network adjusts its parameters to minimize classification error and improve prediction accuracy.

After training, the model is validated and tested using unseen data to evaluate its performance. Metrics such as accuracy, precision, recall, and F1-score are used to assess the effectiveness of the model. This evaluation ensures that the system can reliably classify heart conditions in real-world scenarios.

Finally, the trained model is deployed for real-time classification. The incoming ECG signals from the hardware are processed and fed into the model, which classifies the signals as normal or abnormal. The results are displayed on the LCD and can also be used to generate alerts in case of detected abnormalities. The overall system is designed to be portable, cost-effective, and suitable for continuous monitoring, making it highly useful in remote and resource-constrained environments.

In summary, the methodology integrates embedded systems with deep learning techniques to create an automated, real-time heart disease classification system that enhances early diagnosis and improves healthcare accessibility.

IV. EXISTING SYSTEM

In the current healthcare environment, heart disease detection primarily relies on conventional electrocardiogram (ECG) monitoring systems used in hospitals and diagnostic centers. These systems involve advanced medical equipment that records the electrical activity of the heart and provides detailed reports for diagnosis. Although highly reliable, such systems require skilled healthcare professionals, particularly cardiologists, to interpret the ECG signals and identify abnormalities. This dependence on expert analysis makes the diagnostic process time-consuming and limits accessibility, especially in rural and resource-constrained areas.

Traditional ECG systems are generally bulky, expensive, and designed for clinical use, which restricts their ability to provide continuous monitoring. Patients typically need to visit hospitals or diagnostic labs for periodic check-ups, making it difficult to detect irregular or intermittent cardiac conditions at an early stage. Moreover, these systems often generate raw ECG data without automated classification, leaving the entire diagnostic responsibility to medical experts. This can sometimes lead to delays or inconsistencies in diagnosis, particularly in cases involving subtle abnormalities.

In recent years, some portable ECG devices and wearable health monitoring systems have been introduced to overcome these limitations. While these devices offer improved mobility and convenience, many of them are limited to basic monitoring functions such as heart rate measurement and do not incorporate advanced analytical capabilities. They lack intelligent algorithms for accurate disease classification and often do not utilize deep learning techniques, which are essential for identifying complex patterns in ECG signals.

Earlier automated systems that attempted to classify heart conditions were primarily based on traditional machine learning approaches. These methods require manual feature extraction from ECG signals, which is a complex and time-consuming process. Additionally, manually extracted features may not capture all relevant patterns, leading to reduced classification accuracy compared to modern deep learning models.

Overall, the existing systems face several challenges, including high cost, lack of portability, dependence on expert interpretation, limited real-time analysis, and insufficient integration of intelligent algorithms. These limitations highlight the need for a more efficient, automated, and cost-

Doi:10.48047/ijiee.2026.16.2.14

effective solution for heart disease detection and monitoring.

V. PROPOSED METHODOLOGY

The proposed methodology aims to develop an efficient and intelligent system for heart disease classification using ECG signals integrated with deep neural networks. The system combines embedded hardware components with advanced machine learning techniques to enable real-time monitoring and automated diagnosis of cardiac conditions. The overall methodology is structured into sequential stages including data acquisition, signal preprocessing, deep learning-based classification, and real-time output display.

In the first stage, physiological signals are acquired using biomedical sensors. An ECG sensor is used to capture the electrical activity of the heart, while a MAX30102 sensor measures heart rate and blood oxygen saturation (SpO_2), providing additional health parameters. These sensors are interfaced with an Arduino Uno, which acts as the central data acquisition and control unit. The Arduino collects the raw signals, performs basic processing, and sends the data for further analysis. Simultaneously, an LCD module is used to display real-time readings, allowing users to monitor their health status instantly.

The next stage involves preprocessing of the acquired ECG signals. Since raw ECG data is often affected by noise such as motion artifacts, baseline drift, and power line interference, filtering techniques are applied to improve signal quality. The processed signals are then normalized and segmented into appropriate time windows to prepare them for input into the deep learning model. This step ensures consistency and enhances the performance of the classification system.

Following preprocessing, a deep neural network (DNN) model is employed for feature extraction and classification. Unlike traditional approaches, the DNN automatically learns relevant features from the ECG signals without manual intervention. The model is trained using labeled datasets containing both normal and abnormal ECG patterns. During training, the network optimizes its internal parameters to minimize classification errors and improve accuracy. This enables the system to effectively recognize complex patterns associated with various cardiac conditions.

After training, the model is validated and tested using unseen data to evaluate its performance. Metrics such as accuracy, precision, recall, and F1-score are used to assess the reliability of the system. Once satisfactory performance is achieved, the trained model is deployed for real-time operation.

In the final stage, the system performs real-time classification of incoming ECG signals. The acquired data is processed and fed into the trained model, which classifies the signals as normal or abnormal. The results are displayed on the LCD, and alerts can be generated if any abnormalities are detected. The integration of embedded hardware with deep learning ensures that the system is portable, cost-effective, and suitable for continuous monitoring in both clinical and home environments.

Overall, the proposed methodology provides a robust solution for early detection of heart diseases by combining real-time data acquisition with intelligent analysis, thereby improving healthcare accessibility and diagnostic efficiency.

VI. BLOCK DIAGRAM

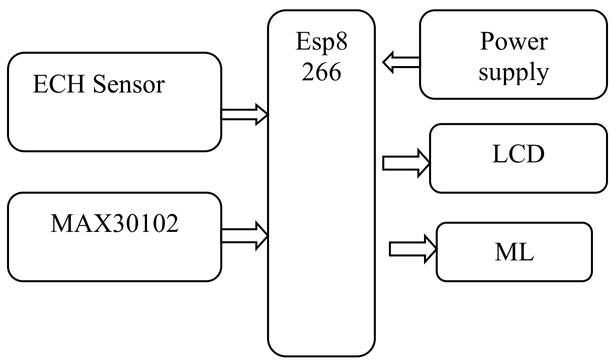

Fig. 6.2. Block Diagram

Doi:10.48047/ijiee.2026.16.2.14

VII. RESULTS AND OUTCOMES

The proposed system for heart disease classification using ECG signals and deep neural networks was successfully designed and implemented, demonstrating effective performance in real-time monitoring and diagnosis. The integration of biomedical sensors with embedded hardware and deep learning techniques enabled accurate acquisition, processing, and classification of physiological signals. The ECG sensor reliably captured the electrical activity of the heart, while the MAX30102 sensor provided additional parameters such as heart rate and blood oxygen saturation, enhancing the overall analysis.

The deep neural network model trained on ECG datasets showed high classification accuracy in distinguishing between normal and abnormal heart conditions. The model was able to automatically extract relevant features from raw ECG signals, eliminating the need for manual feature engineering and improving diagnostic efficiency. Performance evaluation using standard metrics such as accuracy, precision, recall, and F1-score indicated that the system provides reliable and consistent results suitable for practical applications.

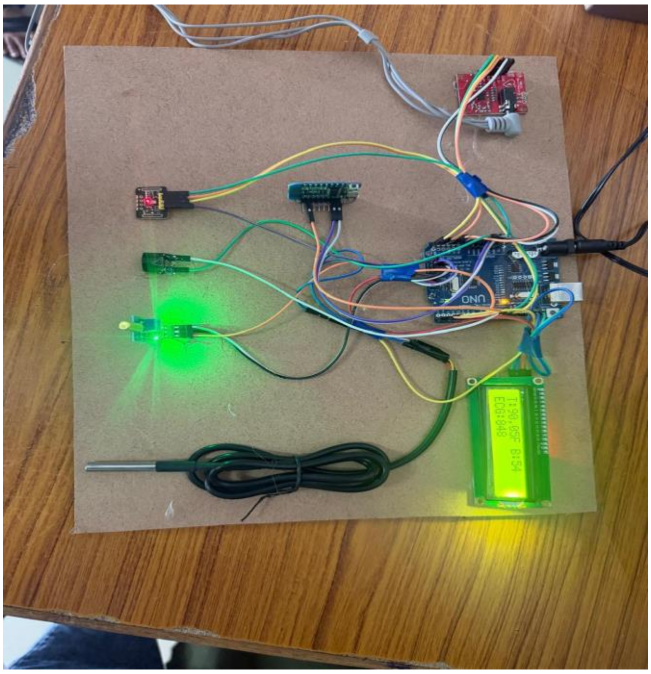

Fig:7.1:Output1

The real-time implementation of the system proved to be effective, as the Arduino-based hardware successfully acquired and transmitted sensor data, while the LCD module displayed instant feedback to the user. The system responded promptly to variations in physiological signals and was capable of identifying abnormal conditions, enabling early warning and timely intervention.

In terms of outcomes, the project achieved a cost-effective, portable, and user-friendly solution for heart health monitoring. The integration of deep learning with embedded systems reduced dependency on manual analysis and specialized medical equipment. The system is particularly beneficial for remote healthcare applications, where continuous monitoring and early detection are essential. Additionally, the scalability of the model allows for further improvements, such as incorporating more complex datasets and expanding classification to multiple heart conditions.

Overall, the results demonstrate that the proposed approach is efficient, accurate, and practical for real-world deployment. The project highlights the

Doi:10.48047/ijiee.2026.16.2.14

potential of combining artificial intelligence with embedded technology to enhance early diagnosis, improve patient care, and increase accessibility to healthcare services.

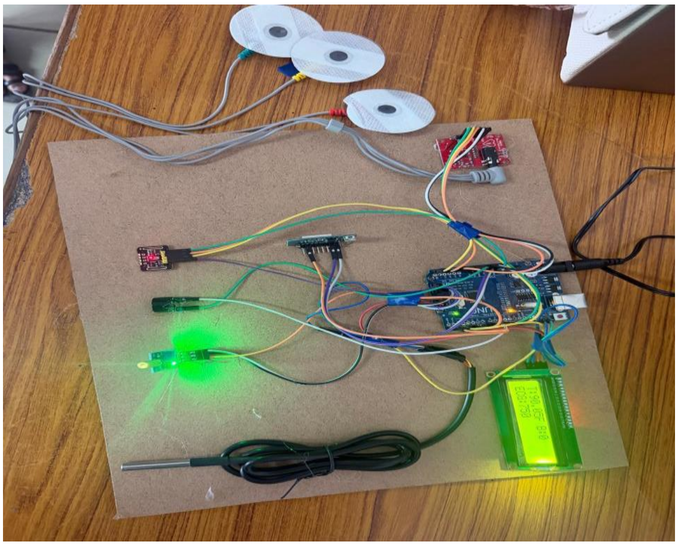

Fig:7.1: Output2

VIII.CONCLUSION

This project presented the design and implementation of a heart disease classification system using ECG signals and deep neural networks. By integrating biomedical sensors with embedded hardware and advanced machine learning techniques, the system provides an efficient solution for real-time monitoring and early detection of cardiac abnormalities. The use of an ECG sensor along with the MAX30102 sensor enabled the collection of multiple physiological parameters, improving the reliability of the analysis.

The deep neural network model demonstrated strong performance in automatically extracting features and accurately classifying heart conditions as normal or abnormal. Unlike traditional methods that rely on manual feature extraction and expert interpretation, the proposed system simplifies the diagnostic process while maintaining high accuracy. The real-time implementation using Arduino and an LCD display further enhances usability by providing immediate feedback to the user.

One of the key advantages of the system is its cost-effectiveness and portability, making it suitable for deployment in remote and resource-limited environments. It reduces the dependency on bulky medical equipment and specialized healthcare professionals, thereby increasing accessibility to continuous heart monitoring.

In conclusion, the proposed approach successfully demonstrates the potential of combining deep learning with embedded systems for intelligent healthcare applications. The system not only improves early diagnosis and monitoring of heart diseases but also lays the foundation for future advancements in smart and connected healthcare solutions. Further enhancements can include expanding the model to classify multiple cardiac conditions and integrating cloud-based monitoring for improved scalability and data accessibility.

REFERENCES

1. Vellela, S. S., & Balamanigandan, R. (2024). Optimized clustering routing framework to maintain the optimal energy status in the wsn mobile cloud environment. Multimedia Tools and Applications, 83(3), 7919-7938.
2. Vellela, S. S., & Balamanigandan, R. (2023). An intelligent sleep-awake energy management system for wireless sensor network. Peer-to-Peer Networking and Applications, 16(6), 2714-2731.
3. Vellela, S. S., & Balamanigandan, R. (2024). An efficient attack detection and prevention approach for secure WSN mobile cloud environment. Soft Computing, 28(19), 11279-11293.
4. Vellela, S. S. (2023). Enhanced speckle noise reduction in breast cancer ultrasound imagery using a hybrid deep learning model. Ingénierie des Systèmes d'Information.
5. Polasi, P. K., Vellela, S. S., Narayana, J. L., Simon, J., Kapileswar, N., Prabu, R. T., & Rashed, A. N. Z. (2026). Data rates transmission, operation performance speed and figure of merit signature for various quadurature light sources under spectral and thermal effects. Journal of Optics, 55(1), 633-643.
6. Praveen, S. P., Nakka, R., Chokka, A., Thatha, V. N., Vellela, S. S., & Sirisha, U. (2023). A novel classification approach for grape leaf disease detection based on different attention deep learning techniques. International Journal of Advanced Computer Science and Applications (IJACSA), 14(6), 2023.

Doi:10.48047/ijiee.2026.16.2.14

7. Vellela, S. S., Rao, M. V., Mantena, S. V., Reddy, M. J., Vatambeti, R., & Rahman, S. Z. (2024). Evaluation of Tennis Teaching Effect Using Optimized DL Model with Cloud Computing System. International Journal of Modern Education and Computer Science (IJMECS), 16(2), 16-28.
8. Vellela, S. S., & Krishna, A. M. (2020). On Board Artificial Intelligence With Service Aggregation for Edge Computing in Industrial Applications. Journal of Critical Reviews, 7(07).
9. Madhuri, A., Jyothi, V. E., Praveen, S. P., Sindhura, S., Srinivas, V. S., & Kumar, D. L. S. (2024). A new multi-level semi-supervised learning approach for network intrusion detection system based on the 'goa'. Journal of Interconnection Networks, 24(supp01), 2143047.
10. Raju, V. V. K., Bhavani, Y. V. K. D., Nandikonda, P., Kareemunnisa, F. N. U., Brahmeswara, K. B., & Sindhura, S. (2026). Iterative and Statistical Analytical Review of Predictive Modeling Approaches in Educational Systems: A Comprehensive Benchmark of AI-Driven Methods. International Journal of Innovative Technology and Interdisciplinary Sciences, 9(1), 490-522.
11. Biyyapu, N., Veerapaneni, E. J., Surapaneni, P. P., Vellela, S. S., & Vatambeti, R. (2024). Designing a modified feature aggregation model with hybrid sampling techniques for network intrusion detection. Cluster Computing, 27(5), 5913-5931.
12. Praveen, S. P., Vellela, S. S., & Balamanigandan, R. (2024). SmartIris ML: harnessing machine learning for enhanced multi-biometric authentication. Journal of Next Generation Technology (ISSN: 2583-021X), 4(1).
13. Vuyyuru, L. R., Purimetla, N. R., Reddy, K. Y., Vellela, S. S., Basha, S. K., & Vatambeti, R. (2025). Advancing automated street crime detection: a drone-based system integrating CNN models and enhanced feature selection techniques. International Journal of Machine Learning and Cybernetics, 16(2), 959-981.
14. Vellela, S. S., Roja, D., Purimetla, N. R., Thalakola, S., Vuyyuru, L. R., & Vatambeti, R. (2025). Cyber threat detection in industry 4.0: Leveraging GloVe and self-attention mechanisms in BiLSTM for enhanced intrusion detection. Computers and Electrical Engineering, 124, 110368.
15. Vellela, S. S., Pushpalatha, D., Sarathkumar, G., Kavitha, C. H., & Harshithkumar, D. (2023). Advanced intelligence health insurance cost prediction using random forest. ZKG International, 8.
16. Vellela, S. S., Babu, B. V., & Mahendra, Y. B. (2024). IoT-based tank water monitoring systems: enhancing efficiency and sustainability. International Journal for Modern Trends in Science and Technology, 10(02), 291-298.
17. Vellela, S. S., Varshini, K., Jeevana, M., Kadheer, S. K., & Kumar, T. P. (2024). Iot based smart irrigation and controlling system. IoT Based Smart Irrigation and Controlling System, International Journal for Modern Trends in Science and Technology, 10(02), 77-85.
18. Vellela, S. S., Chaganti, A., Gadde, S., Bachina, P., & Karre, R. (2022). A Novel Approach for Detecting Automated Spammers in Twitter. Mukt Shabd, 11, 49-53.
19. Vellela, S. S., Narapasetty, S., Somepalli, M., Merikapudi, V., & Pathuri, S. (2022). Fake News Articles Classifying Using Natural Language Processing to Identify in-article Attribution as a Supervised Learning Estimator. Mukt Shabd Journal, 11.
20. Vellela, S. S., Vineeth, S., & Suresh, V. (2024). IoT Based ICU Patient Monitoring System. IoT Based ICU Patient Monitoring System, International Journal for Modern Trends in Science and Technology, 10(02), 265-273.
21. Vellela, S. S., & Balamanigandan, R. (2025). Designing a Dynamic News App Using Python. Available at SSRN 5250912.
22. Vellela, S. S., Rao, M. V., Krishna, C. V. M., Rao, T. S., & Dasthavejula, R. (2026). Piezoelectric and Shape-Memory Materials for Actuators and Energy Harvesting in

Doi:10.48047/ijiee.2026.16.2.14

Mechanical, Electronics, and Biomedical Engineering Using AI-Based Design. In Advanced Materials for Biomedical Devices (pp. 195-206). CRC Press.

23. Vellela, S. S., Singu, K., Kakarla, L. S., Tadikonda, P., & Sattenapalli, S. N. R. (2025). NLP-Driven Summarization: Efficient Extraction of Key Information from Legal and Financial Documents. Available at SSRN 5250908.
24. Vellela, S. S., Anusha, P., Vullam, N. R., Jala, J., Bellapu, V. S., & Vindhya, A. S. (2025, October). Quantum Cryptography and Key Distribution for Secure Communication in the Post Quantum World. In 2025 International Conference on Sustainable Communication Networks and Application (ICSCN) (pp. 619-624). IEEE.
25. Roja, D., Jidugu, S. K., Rao, T. S., Vuyyuru, L. R., Vellela, S. S., & Ranjani, B. S. (2025, December). High-Fidelity Image Synthesis using Enhanced Generative Adversarial Networks with Attention Mechanisms. In 2025 International Conference on NexGen Networks and Cybernetics (IC2NC) (pp. 885-890). IEEE.
26. Vellela, S. S., Vuyyuru, L. R., Jidugu, S. K., Rao, M. P., & Srinivas, B. R. (2025, November). The Impact Of Quantum Computing On Blockchain Security And Quantum Resistant Protocols. In 2025 2nd International Conference on Intelligent Systems for Cybersecurity (ISCS) (pp. 1-6). IEEE.
27. Yanamadala, N., & Vellela, S. S. (2025, June). Ensuring Authenticity and Confidentiality in Images using SHA-ECC Fusion. In 2025 Second International Conference on Networks and Soft Computing (ICNSoC) (pp. 684-689). IEEE.
28. Vellela, S. S. (2024). A Comprehensive Review of AI Techniques in Serious Games: Decision Making and Machine Learning.
29. Burra, R. S., APCV, G. R., & Vellela, S. S. (2024). Strategic Insights: Unleashing the Power of Big Data Analytics for Credit Investigation and Risk Mitigation in Commercial Banking. International Journal of Progressive Research in Engineering Management and Science, 4(01), 458-464.
30. Vellela, S. S., Purimetla, N. R., Vindhya, A. S., Vullam, N. R., Srinivas, B. R., & Vuyyuru, L. R. (2025, October). Design and Simulation of Quantum Error Correction Codes for Scalable Quantum Architectures. In 2025 7th International Conference on Innovative Data Communication Technologies and Application (ICIDCA) (pp. 1570-1575). IEEE.
31. Vellela, S. S., Purimetla, N. R., Rao, P. V., Daniel, V. A. A., Koppolu, H. K. R., & Janani, B. (2025). AI-Enabled Wearable Hemodynamic Monitoring System for Early Identification of Thrombotic Events. Vascular and Endovascular Review, 8(16s), 321-336.
32. Venkatesh, N., Maheswari, S., & Triveni, P. (2024). Harnessing IoT for Real-Time Plant Health Monitoring: Challenges and Opportunities.
33. Reddy, B. V., Kumar, A. H., Gopi, C., Prasad, Y. V. D., Vellela, S. S., & Roja, D. (2025, April). Machine learning based automated liver fibrosis stage diagnosis with prediction. In 2025 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE) (pp. 1-6). IEEE.
34. Rao, M. V., Sreeraman, Y., Mantena, S. V., Gundu, V., Roja, D., & Vatambeti, R. (2024). Brinjal Crop yield prediction using Shuffled shepherd optimization algorithm based ACNN-OBDLSTM model in Smart Agriculture. Journal of Integrated Science and Technology, 12(1), 710-710.
35. Haritha, K., Geethika, N. S., Venkateswarlu, K., Kumar, R. H., & Ramakrishna, Y. Enhancing Public Safety with AI & ML-Based CCTV Surveillance.
36. Haritha, K., Prakash, P. B., Pravallika, D., Venkatesh, K., & Venkatesh, G. Enhancing Object Detection in Autonomous Vehicles Under Low-Light Conditions Using Federated Learning and YOLOv5.
37. Ram, C. S., Vellela, S. S., Sravanthi Javvadi, D. V., Rashid, S. Z., & Madhumathi, S. M. (2025). Integrated Robotic–Imaging Platforms in

Doi:10.48047/ijiee.2026.16.2.14

Endovascular Surgery: Current Capabilities and Future Directions. Vascular and Endovascular Review, 8(16s), 285-298.

38. Roja, D., Navya, G., Srujana, B. S., Mamatha, P., & Sai, C. Y. K. Deep Learning for Hotel Reviews: A Framework for Sentiment Classification and Fake Review Detection.
39. Pakalapati, S., Rani, C. J., Vellela, S. S., Thanuja, N., & Bindu, M. N. H. (2025, November). Progressive GAN-based Framework for Realistic Image Generation and Style Transfer. In 2025 5th International Conference on Evolutionary Computing and Mobile Sustainable Networks (ICECMSN) (pp. 474-479). IEEE.
40. Balamanigandan, R., Vellela, S. S., Gorintla, S., Vuyyuru, L. R., Thanuja, N., & Rao, T. S. (2025, September). Quantum-Enhanced Data Security for Electronic Health Records: A Framework for Post-Quantum Cryptography in Healthcare Systems. In 2025 6th International Conference on Smart Electronics and Communication (ICOSEC) (pp. 1924-1929). IEEE.
41. Roja, D., Amulya, P., Nagasai, M., Prasad, D. D., & Babu, A. V. Machine Learning-Based Early Diagnosis of Fish Diseases via Water Quality Data.
42. Sai, M. B., & Vellela, S. S. (2025, December). Hybrid ML Driven Multi-Cloud Service Work Load Prediction For Financial Systems. In 2025 1st International Conference on Advancement in Futuristic Technologies (ICAFT) (pp. 1-6). IEEE.
43. Kareemunnisa, D., Haritha, K., Ranjani, B. S., Venkateswarlu, K., & Bindu, M. N. H. DUAL-STAGE PRIVACY PROTECTION FOR GRAPH NEURAL NETWORKS AGAINST INFERENCE ATTACKS.
44. Mandava, R., Haritha, K., Vellela, S. S., Purimetla, N. R., Mohan, B. K., & Harinadh, T. (2025, June). Analysing User Perceptions of Trust in Financial Systems Using Explainable AI. In 2025 Second International Conference on Networks and Soft Computing (ICNSoC) (pp. 26-30). IEEE.

Doi:10.48047/ijiee.2026.16.2.14