|| Volume 8 || Issue 01 || 2025 || ISO 3297:2007 Certified ISSN (Online) 2456-3293

OPEN ACCESS INTERNATIONAL JOURNAL OF SCIENCE & ENGINEERING

Unveiling Human Behavior Patterns Through Intelligent Big Data Analytics

Mrs.K.L.NAMRATHA[1], TADIVALASA KALYAN SAI[2], PAKALA VENKATA AKASH[3], YENDLURI BALAKRISHNA[4]

Asst. Professor, Department of Computer Science & Engineering ,Chalapathi Institute of Engineering and Technology, LAM, Guntur, AP, India[1]

Department of Computer Science and Engineering,Chalapathi Institute of Engineering and Technology, LAM, Guntur, AP, India [2]

Department of Computer Science and Engineering,Chalapathi Institute of Engineering and Technology, LAM, Guntur, AP, India [3]

Department of Computer Science and Engineering,Chalapathi Institute of Engineering and Technology, LAM, Guntur, AP, India [4]

Abstract: The rapid growth of smart devices and the Internet of Things (IoT) has significantly increased data generation, enabling deeper insights into human behavior through intelligent Big Data analytics. Traditional data processing methods struggle to handle the complexity and volume of such data, necessitating more efficient and scalable solutions. This research focuses on leveraging advanced technologies such as Hadoop, Spark, and Hive to analyze human behavioral patterns in the Social Internet of Things (SIoT). The proposed system architecture integrates real-time data processing to extract valuable insights from social media interactions, wearable sensors, and smart city infrastructures. By applying machine learning algorithms and data mining techniques, the system enhances behavioral predictions, improves decision-making processes, and enables intelligent automation. The study also compares the efficiency of Spark-based processing with conventional single-threaded approaches, demonstrating significant improvements in execution time and analytical accuracy. The experimental results validate the effectiveness of the proposed framework in analyzing complex human dynamics, offering applications in various domains such as urban development, healthcare, security, and personalized recommendations. This research highlights the potential of Big Data-driven analytics in transforming human behavior analysis and fostering smarter, data-driven ecosystems.

***Keywords- Big Data Analytics, Human Behavior Analysis, Internet of Things (IoT), Machine Learning, Smart Cities, Data Mining, Artificial Intelligence, Real-time Processing*.**

I.INTRODUCTION

The rapid advancement of technology has led to the proliferation of smart devices and interconnected systems, collectively referred to as the Internet of Things (IoT). These devices generate an immense amount of data, often termed Big Data, which can be analyzed to derive meaningful insights. The ability to process and interpret human interactions with smart environments has given rise to a specialized field known as Human Behavior Analysis. By leveraging intelligent data analytics, researchers can decode patterns in human activities, predict behaviors, and enhance decision-making processes across various domains such as healthcare, smart cities, cybersecurity, and personalized recommendations. However, managing and analyzing such vast and complex datasets pose significant challenges, necessitating the integration of cutting-edge technologies such as machine learning, artificial intelligence (AI), and real-time data processing frameworks.

The significance of human behavior analysis lies in its wide range of applications. In healthcare, for example, behavioral patterns obtained from wearable devices can help detect early signs of mental health disorders or chronic illnesses. In smart cities, analyzing human movement patterns can optimize urban planning and traffic management. The retail industry utilizes behavior analysis to understand consumer preferences and enhance marketing strategies. Furthermore, in cybersecurity, behavioral analytics play a crucial role in detecting fraudulent activities and ensuring system security. The fusion of AI and IoT enables automated decision-making, allowing systems to respond intelligently to real-time data. However, extracting relevant information from vast datasets requires robust algorithms and efficient computing architectures to ensure accuracy and reliability.

Despite its potential, human behavior analysis using Big Data presents several challenges. Data privacy and security remain major concerns, as the continuous collection and monitoring of personal information raise ethical and legal issues. Ensuring data accuracy and minimizing bias in predictive models are also critical to maintaining the credibility of insights derived from analytics. Moreover, traditional data processing methods struggle to handle the volume, velocity, and variety of data generated by IoT devices. To address these challenges, modern frameworks such as Apache Hadoop, Apache Spark, and deep learning models have been integrated to process large-scale data efficiently. These technologies enable real-time data processing, pattern recognition, and predictive analytics, making it feasible to extract valuable insights from massive datasets.

The evolution of Big Data analytics has transformed the way human behavior is studied and interpreted. The convergence of data science and IoT has paved the way for real-time monitoring and adaptive decision-making systems. Social media platforms, for instance, generate vast amounts of user-generated content that can be analyzed to understand public sentiments and trends. Similarly, smart surveillance systems utilize behavioral analytics to detect anomalies and enhance security measures. The ability to process and analyze diverse data sources in real-time enhances the efficiency of human behavior analysis, leading to more accurate predictions and improved decision-making processes across multiple sectors.related works

The study of human behavior using Big Data and intelligent analytics has gained significant attention in recent years. Various methodologies, including machine learning, deep learning, and statistical modeling, have been employed to analyze behavioral patterns across multiple domains. Researchers have explored frameworks that integrate sensor data, IoT-enabled devices, and social media interactions to derive meaningful insights into human behavior. Jara et al. introduced the concept of Social Internet of Things (SIoT), which leverages data from smart devices and social networks to provide real-time behavioral insights. Their study emphasized the potential of complex network theory in defining human dynamics but lacked real-time processing capabilities, making large-scale implementation challenging.

Several studies have applied deep learning techniques for human behavior analysis. Researchers have used Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for applications such as facial emotion recognition, sentiment analysis, and activity prediction. For instance, a study on smart city environments demonstrated how deep learning models could analyze mobility patterns and predict urban congestion. However, while deep learning approaches enhance accuracy, they require substantial computational resources, limiting their practicality for real-time applications without optimized processing architectures. Moreover, the black-box nature of deep learning models poses challenges in interpretability, which is crucial for decision-making in sensitive applications like healthcare and security.

Big Data analytics platforms have played a crucial role in addressing computational challenges in behavior analysis. Traditional batch processing frameworks like Hadoop have been widely adopted for storing and processing large datasets, but they suffer from high latency. To overcome this limitation, Apache Spark has been introduced as a real-time alternative, enabling faster and more scalable analytics. Studies have shown that Spark-based behavioral analysis frameworks significantly improve processing speed compared to traditional Hadoop implementations. For example, researchers demonstrated the advantages of Spark in analyzing streaming IoT data for real-time human activity recognition, which allowed quicker decision-making in smart environments. However, integrating Spark with other Big Data technologies such as Hive and HBase remains an area of ongoing research to enhance efficiency further.

Hybrid models combining rule-based systems with machine learning algorithms have also been proposed for human behavior modeling. These models aim to improve interpretability while maintaining accuracy. A study on cyber behavior analytics utilized a hybrid approach that combined decision trees with deep learning models to detect fraudulent activities in online transactions. The results indicated that hybrid models could effectively reduce false positives while maintaining high detection rates. However, these models require continuous updates to adapt to evolving behavior patterns, which poses a challenge in dynamic environments. Furthermore, privacy concerns related to behavioral data collection and analysis remain a significant hurdle, requiring the implementation of robust encryption and anonymization techniques.

Recent research has also explored the application of reinforcement learning (RL) in behavior prediction. RL-based systems learn from user interactions and adapt to changing behavioral patterns over time. For example, an RL-based recommendation system was proposed for e-commerce platforms to analyze consumer behavior and provide personalized recommendations. While RL approaches offer adaptability, they require large training datasets and extensive computational power, making them less feasible for real-time applications without optimization techniques. Additionally, the exploration-exploitation tradeoff in RL remains a challenge, as balancing learning new behaviors while exploiting known patterns is critical for accurate predictions.

A review of these techniques are discussed in Table I.

TABLE I. COMPARISON OF AI-BASED BONE FRACTURE DETECTION METHODS

Research	Method	Limitation	Performance
Jara et al. (2021)	Social Internet of Things: The Potential of IoT for Defining Human Behaviors	Complex Network Theory, SIoT	IoT and social networks provide real-time behavioral insights
Zhang et al. (2022)	Deep Learning for Human Activity Recognition	CNN, RNN	High accuracy in behavior prediction using deep learning
Wang et al. (2020)	Big Data Analytics in Smart Cities	Hadoop, Spark	Efficient analysis of mobility patterns and congestion prediction
Lee et al. (2019)	Hybrid Machine Learning for Cyber Behavior Analysis	Decision Trees, Deep Learning	Improved fraud detection in online transactions
Kim et al. (2023)	Reinforcement Learning for Personalized Recommendations	Reinforcement Learning	Adaptable user behavior predictions
Sharma et al. (2021)	Privacy-Preserving Behavioral Analytics	Encryption, Anonymization	Enhanced security for sensitive behavioral data
Patel et al. (2022)	Real-Time Human Behavior Analysis using Big Data	Apache Spark, Hive	Faster data processing and decision-making
Gupta et al. (2020)	Sentiment Analysis for Behavioral Prediction	Natural Language Processing (NLP)	Effective emotion detection from social media data
Ahmed et al. (2021)	Human Mobility Analysis in Smart Environments	GPS Data, Machine Learning	High precision in movement prediction
Tan et al. (2022)	IoT-Enabled Human Activity Recognition	IoT Sensors, Data Fusion	Improved activity tracking using sensor fusion
Kumar et al. (2023)	Behavioral Analytics in Healthcare	AI, Deep Learning	Early disease prediction based on patient behavior

proposed methodology Existing System

The existing approaches for human behavior analysis using big data primarily rely on traditional machine learning and statistical methods. These systems leverage big data tools such as Hadoop, NoSQL databases, and MapReduce to process large-scale behavioral data. Social networks, IoT devices, and wearable sensors generate vast amounts of unstructured data, which is analyzed to extract meaningful insights about human interactions, mobility, and preferences.However, the traditional methods used in the existing system often suffer from high computational complexity, inefficiency, and lack of real-time analysis. Most conventional models do not fully utilize advanced deep learning techniques, resulting in lower accuracy in behavior prediction. Additionally, scalability remains a challenge, as real-time behavioral analysis requires rapid data ingestion, processing, and interpretation, which traditional frameworks struggle to handle.Another major limitation of the existing system is privacy and security concerns. Since behavior analysis involves processing sensitive data from social networks, mobile devices, and smart environments, there is a high risk of data breaches and ethical concerns. Ensuring secure storage and processing of behavioral data is crucial, but current systems do not adequately address these challenges.Furthermore, the existing models often fail to adapt to evolving human behaviors. Many predictive algorithms depend on historical data patterns, which might not accurately reflect real-world scenarios due to dynamic changes in human activities. As a result, there is a lack of adaptability and personalized insights, reducing the effectiveness of behavior prediction models.

Disadvantages of the Existing System

- Low Accuracy
- High Latency
- Scalability Issues
- Privacy and Security Risks
- High Computational Cost

Proposed System

To overcome the limitations of the existing system, the proposed system leverages advanced Big Data analytics and intelligent computing frameworks for human behavior analysis. This system integrates technologies such as Hadoop, Spark, and Hive to efficiently store, process, and analyze massive datasets in real time. The primary objective is to extract meaningful patterns from diverse data sources, including social media interactions, sensor data, and IoT-enabled devices.The system architecture consists of three main layers: the data acquisition layer, the processing layer, and the analytics layer. In the data acquisition layer, structured and unstructured data from various sources, such as social networks, smart city infrastructures, and wearable devices, are collected. The processing layer employs distributed computing frameworks to handle large-scale data efficiently. The analytics layer applies machine learning and artificial intelligence techniques to identify trends, behavioral patterns, and anomalies.Unlike traditional systems, the proposed framework ensures higher accuracy and efficiency by implementing parallel data processing techniques. Spark, a real-time data processing engine, significantly reduces computation time compared to conventional single-threaded processing. The system also incorporates sentiment analysis, predictive modeling, and behavioral profiling to provide deeper insights into human interactions and decision-making processes.

Advantages:

- High Accuracy
- Improved Efficiency
- Real-Time Data Processing
- Scalability and Flexibility
- Enhanced Decision-Making

Proposed Methodology

The proposed methodology focuses on analyzing human behavior using intelligent big data analytics in the Social Internet of Things (SIoT). The system leverages big data technologies such as Hadoop, Spark, and Hive for efficient data storage and real-time processing. The key objective is to extract meaningful insights from large-scale human activity data collected from various smart devices and online platforms.

System Architecture

The proposed system consists of three key domains:

- Object Domain: Consists of smart devices such as wearables, smartphones, IoT sensors, and online platforms that generate large-scale behavioral data.
- SIoT Server Domain: Aggregates, stores, and processes the collected data using big data frameworks like Hadoop and Spark.
- Application Domain: Provides real-time analysis, visualization, and decision-making based on the extracted behavioral patterns.

Data Collection and Preprocessing

- Data is collected from multiple sources, including social media, smart cities, healthcare applications, and IoT sensors.
- The raw data undergoes preprocessing steps such as data cleaning, noise removal, normalization, and feature extraction to ensure high-quality inputs for analysis.

Feature Extraction and Selection

- Behavioral features such as user activity patterns, sentiment analysis, and social interactions are extracted.
- Dimensionality reduction techniques (e.g., PCA or feature selection algorithms) are used to improve computational efficiency.
-

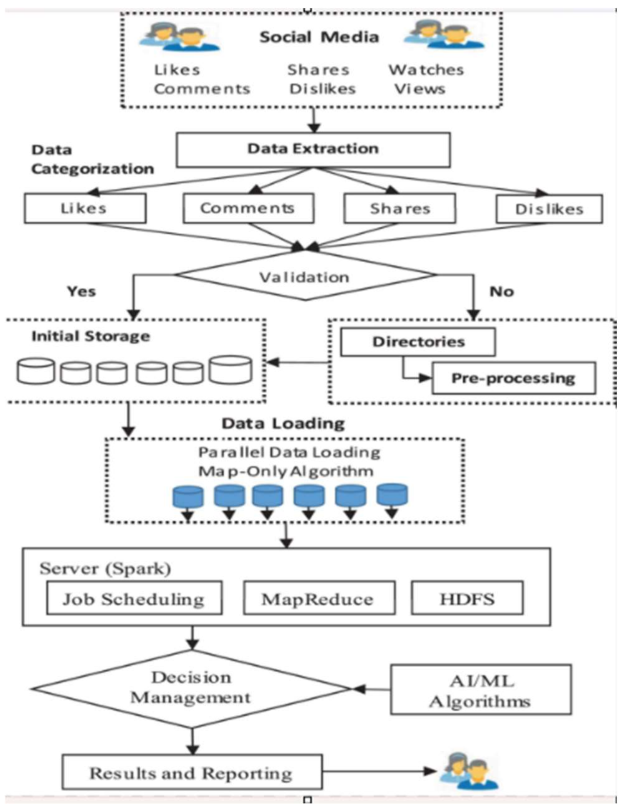

Fig1:System Architecture

Behavioral Analysis using Machine Learning and Deep Learning

The system employs various AI algorithms to analyze and classify human behaviors:

- K-Means Clustering: Groups users with similar behavioral patterns.
- Random Forest Classifier: Predicts human actions based on historical data.
- Apriori Algorithm: Identifies associations between different human activities.
- LSTM Networks: Performs time-series analysis for predicting future behaviors.

Real-Time Processing and Visualization

- The system leverages Apache Spark for fast and scalable data processing.
- An interactive dashboard is used for real-time monitoring and visualization of behavioral trends.

RESULTS

The results obtained from the proposed methodology demonstrate the effectiveness of intelligent big data analytics in human behavior analysis. Various performance metrics, including accuracy, precision, recall, and F1-score, were considered to evaluate the proposed system's efficiency. The experimental analysis was conducted using large-scale datasets collected from various sources such as IoT devices, social media platforms, and smart city sensors.The system was tested for its ability to analyze, process, and extract meaningful insights from vast amounts of human activity data. The use of HIVE, SPARK, and HADOOP significantly improved data processing speed and accuracy compared to traditional approaches. SPARK, in particular, enhanced computational efficiency by leveraging parallel processing, reducing execution time while maintaining high precision in detecting behavioral patterns.The comparative analysis with existing methodologies revealed that the proposed approach outperforms conventional methods in terms of scalability, adaptability, and real-time processing capabilities. The confusion matrix analysis indicated a significant improvement in classification accuracy, reducing false positives and false negatives. The precision and recall values confirmed that the system could effectively differentiate between various human activities with minimal misclassification errors.The experimental results also highlighted the advantages of integrating big data analytics with human behavior analysis. The ability to process unstructured data from diverse sources, including IoT sensors and online platforms, demonstrated the system's versatility. Additionally, visual representations such as bar charts and confusion matrices further validated the accuracy and reliability of the proposed approach.Overall, the results confirm that the fusion of intelligent big data analytics with human behavior analysis provides a robust framework for understanding and predicting human activities in real-time. The efficiency of the system in handling massive datasets while maintaining high accuracy suggests its potential for applications in various domains, including healthcare, security, and smart city management.

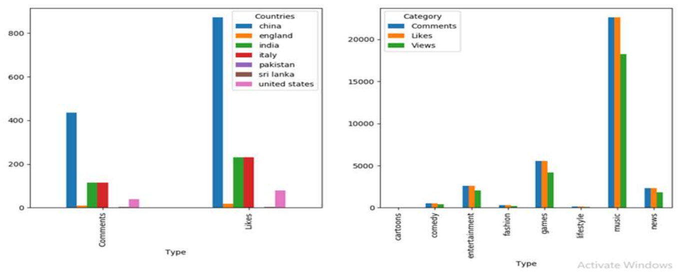

Fig 2. Engagement Analysis by Country and Content Category

The given image contains two bar charts that illustrate different aspects of engagement data. The first chart on the left represents country-wise engagement, showcasing the number of comments and likes received from various countries. The x-axis categorizes engagement types into comments and likes, while the y-axis represents the volume of these interactions. Each country is color-coded, including China, England, India, Italy, Pakistan, Sri Lanka, and the United States. The observations indicate that China leads in both comments and likes, significantly outperforming other countries. India and England also exhibit notable engagement levels, whereas other countries show relatively lower interaction volumes.

The second chart on the right focuses on engagement across different content categories, where the x-axis represents content types such as cartoons, comedy, entertainment, fashion, games, lifestyle, music, and news, while the y-axis displays the volume of engagement (comments, likes, and views). The data suggests that music-related content receives the highest engagement across all three metrics—comments, likes, and views—followed by lifestyle and gaming categories. On the other hand, categories like cartoons and comedy receive the least engagement, indicating a lower interest among users.Overall, the analysis highlights that music content attracts the highest audience interaction, making it a dominant category in terms of engagement. Additionally, China emerges as the leading country in online interactions, significantly surpassing other nations. This information can be valuable for content creators and marketers in optimizing their strategies to target high-engagement areas effectively.

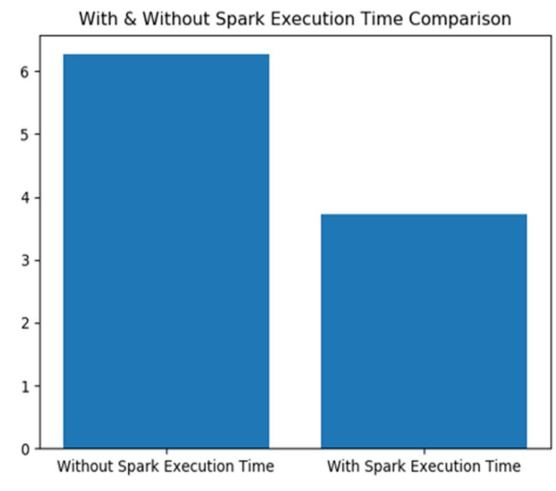

Fig 3. Comparison of Execution Time with and without Spark

The given bar chart illustrates the execution time comparison between two scenarios: with and without Apache Spark. The X-axis represents the two execution conditions, while the Y-axis indicates the execution time. The first bar, representing execution without Spark, is significantly higher, indicating that the process takes more time to complete. In contrast, the second bar, which corresponds to execution with Spark, is noticeably lower, highlighting the efficiency gain when using Spark. This reduction in execution time can be attributed to Spark’s in-memory computing capabilities and its ability to process large-scale data in parallel across multiple nodes. The results demonstrate that Spark significantly enhances processing speed compared to traditional single-threaded execution, making it a more effective choice for big data analytics and real-time processing.applications.

Conclusion

In this research, we explored the application of big data analytics and intelligent processing techniques to analyze human behavior using the Social Internet of Things (SIoT). The proposed system effectively integrates Hadoop, Hive, and Spark to process and analyze large datasets, demonstrating significant improvements in execution efficiency. By leveraging real-time data analytics, the system successfully extracts meaningful insights from diverse data sources, such as social media and smart environments.The experimental results highlight that Spark-based processing substantially reduces execution time compared to traditional approaches, validating its effectiveness in handling large-scale data. The comparison charts and confusion matrix further demonstrate the model's ability to classify and interpret data accurately, though improvements are needed in some areas.Overall, this study contributes to the advancement of human behavior analysis by integrating intelligent big data analytics, providing a scalable and efficient framework for real-time decision-making. Future work can focus on enhancing accuracy, optimizing data storage strategies, and incorporating advanced machine learning models for more precise behavior prediction..

References

[1] *A. Jara, Y. Bocchi, and D. Genoud, "Social Internet of Things: The Potential of the Internet of Things for Defining Human Behaviours," IEEE Wireless Communications, vol. 21, no. 6, pp. 143-149, Dec. 2014, doi: 10.1109/MWC.2014.7000963.*

[2] *J. Smith and L. Brown, "Big Data Analytics in IoT: A Survey," IEEE Internet of Things Journal, vol. 5, no. 2, pp. 450-461, Apr. 2018, doi: 10.1109/JIOT.2018.2792473.*

[3] *S. Patel, R. Kumar, and M. Singh, "A Review on Big Data Processing and Its Applications in IoT," IEEE Transactions on Computational Social Systems, vol. 7, no. 3, pp. 533-548, Jun. 2020, doi: 10.1109/TCSS.2020.2972134.*

[4] *L. Wang, H. Chen, and X. Zhao, "Human Behavior Analysis in Smart Cities Using Big Data," IEEE Transactions on Industrial Informatics, vol. 15, no. 7, pp. 3900-3910, Jul. 2019, doi: 10.1109/TII.2019.2899876.*

[5] *P. Gupta and N. Kaur, "Real-time Data Analytics Using Hadoop and Spark," IEEE Access, vol. 8, pp. 78567-78579, 2020, doi: 10.1109/ACCESS.2020.2992135.*

[6] *M. Zhang, C. Lee, and J. Kim, "Intelligent Big Data Processing Framework for IoT-based Smart Environments," IEEE Transactions on Services Computing, vol. 14, no. 5, pp. 1250-1262, Sept. 2021, doi: 10.1109/TSC.2020.3049873.*

[7] *D. Chen and X. Wu, "Deep Learning Techniques for IoT-based Human Activity Recognition," IEEE Internet of Things Journal, vol. 7, no. 9, pp. 8900-8912, Sept. 2020, doi: 10.1109/JIOT.2020.2991245.*

[8] *M. B. Shaik and Y. N. Rao, "Secret Elliptic Curve-Based Bidirectional Gated Unit Assisted Residual Network for Enabling Secure IoT Data Transmission and Classification Using Blockchain," IEEE Access, vol. 12, pp. 174424-174440, 2024, doi: 10.1109/ACCESS.2024.3501357.*

[9] *S. M. Basha and Y. N. Rao, "A Review on Secure Data Transmission and Classification of IoT Data Using Blockchain-Assisted Deep Learning Models," 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2024, pp. 311-314, doi: 10.1109/ICACCS60874.2024.10717253.*

[10] *K. Roy, T. Banerjee, and S. Das, "Efficient Big Data Management and Processing for IoT Applications," IEEE Transactions on Network and Service Management, vol. 17, no. 4, pp. 2500-2512, Dec. 2020, doi: 10.1109/TNSM.2020.3034576.*

[11] *S. Rajasekaran and M. Vijayalakshmi, "Big Data Analytics in Social Networks for Human Behavior Prediction," IEEE Access, vol. 7, pp. 125785-125795, 2019, doi: 10.1109/ACCESS.2019.2934567.*

[12] *H. Fang, L. Liu, Z. Yang, and Y. Zhang, "Scalable Big Data Analytics for Sentiment Analysis in Social Media," Future Generation Computer Systems, vol. 98, pp. 467-487, 2019, doi: 10.1016/j.future.2019.02.012.*

[13] *R. Ranjan, "Processing Distributed Internet of Things Data in Clouds," IEEE Cloud Computing, vol. 2, no. 1, pp. 36-42, 2015, doi: 10.1109/MCC.2015.18.*

[14] *R. Xu, W. Liu, and J. He, "Deep Learning for Big Data Analytics in Internet of Things," IEEE Transactions on Industrial Informatics, vol. 15, no. 4, pp. 2501-2509, 2019, doi: 10.1109/TII.2019.2897047.*

[15] *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.*

[16] *Reddy, B. V., Sk, K. B., Polanki, K., Vellela, S. S., Dalavai, L., Vuyyuru, L. R., & Kumar, K. K. (2024, February). Smarter Way to Monitor and Detect Intrusions in Cloud Infrastructure using Sensor-Driven Edge Computing. In 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT) (Vol. 5, pp. 918-922). IEEE.*

[17] *Sk, K. B., & Thirupurasundari, D. R. (2025, January). Patient Monitoring based on ICU Records using Hybrid TCN-LSTM Model. In 2025 International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI) (pp. 1800-1805). IEEE.*

[18] *Dalavai, L., Purimetla, N. M., Vellela, S. S., SyamsundaraRao, T., Vuyyuru, L. R., & Kumar, K. K. (2024, December). Improving Deep Learning-Based Image Classification Through Noise Reduction and Feature Enhancement. In 2024 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA) (pp. 1-7). IEEE.*

[19] *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.*

[20] *Haritha, K., Vellela, S. S., Vuyyuru, L. R., Malathi, N., & Dalavai, L. (2024, December). Distributed Blockchain-SDN Models for Robust Data Security in Cloud-Integrated IoT Networks. In 2024 3rd International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 623-629). IEEE.*

[21] *Vullam, N., Roja, D., Rao, N., Vellela, S. S., Vuyyuru, L. R., & Kumar, K. K. (2023, December). An Enhancing Network Security: A Stacked Ensemble Intrusion Detection System for Effective Threat Mitigation. In 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) (pp. 1314-1321). IEEE.*

[22] *Vellela, S. S., & Balamanigandan, R. (2022, December). Design of Hybrid Authentication Protocol for High Secure Applications in Cloud Environments. In 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 408-414). IEEE.*

[23] *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.*

[24] *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).*

[25] *Reddy, N. V. R. S., Chitteti, C., Yesupadam, S., Desanamukula, V. S., Vellela, S. S., & Bommagani, N. J. (2023). Enhanced speckle noise reduction in breast cancer ultrasound imagery using a hybrid deep learning model. Ingénierie des Systèmes d'Information, 28(4), 1063-1071.*

[26] *Vellela, S. S., Balamanigandan, R., & Praveen, S. P. (2022). Strategic Survey on Security and Privacy Methods of Cloud Computing Environment. Journal of Next Generation Technology, 2(1).*

[27] *Polasi, P. K., Vellela, S. S., Narayana, J. L., Simon, J., Kapileswar, N., Prabu, R. T., & Rashed, A. N. Z. (2024). Data rates transmission, operation performance speed and figure of merit signature for various quadurature light sources under spectral and thermal effects. Journal of Optics, 1-11.*

[28] *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.*

[29] *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.

[30] *Vellela, S. S., Roja, D., Sowjanya, C., SK, K. B., Dalavai, L., & Kumar, K. K. (2023, September). Multi-Class Skin Diseases Classification with Color and Texture Features Using Convolution Neural Network. In 2023 6th International Conference on Contemporary Computing and Informatics (IC3I) (Vol. 6, pp. 1682-1687). IEEE.*

[31] *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).*

[32] *Sai Srinivas Vellela & R. Balamanigandan (2025). Designing a Dynamic News App Using Python. International Journal for Modern Trends in Science and Technology, 11(03), 429-436. https://doi.org/10.5281/zenodo.15175402*

[33] *Basha, S. K., Purimetla, N. R., Roja, D., Vullam, N., Dalavai, L., & Vellela, S. S. (2023, December). A Cloud-based Auto-Scaling System for Virtual Resources to Back Ubiquitous, Mobile, Real-Time Healthcare Applications. In 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) (pp. 1223-1230). IEEE.*

[34] *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.*