SENTIMENT ANALYSIS OF COMMENTS RECIVED THROUGH E-CONSULTATION MODULE

[1]B. INDRA DEVI,[2]PALAGANI LIKHITHA, [3]RAJULAPATI NAVYA SRI, [4]T.H.VENKATA SATYAMARUTHI SUMANTH

[1]Assistant Professor, [234]Students, Department of Computer Science and Engineering, SRI VASAVI INSTITUTE OF ENGINEERING & TECHNOLOGY, NANDAMURU, ANDHRA PRADESH

ABSTRACT

Sentiment analysis has emerged as an essential technique for understanding public opinion in digital communication platforms. Government and organizational e-consultation modules enable citizens and users to submit feedback, suggestions, and complaints online. However, the large volume of textual comments generated through these platforms makes manual analysis difficult and time-consuming. This study proposes a sentiment analysis system for automatically classifying comments received through an e-consultation module into positive, negative, and neutral categories using machine learning and natural language processing techniques. The system utilizes text preprocessing methods such as tokenization, stop-word removal, stemming, and vectorization to prepare textual data for classification. Machine learning models are implemented using Python-based frameworks including TensorFlow, Keras, and Natural Language Toolkit (NLTK). The backend of the system is developed using Flask, while React is used for the user interface and MySQL for storing user comments and processed results. The proposed system enables administrators and decision-makers to quickly interpret public sentiment, identify major concerns, and prioritize issues based on collective feedback. The architecture incorporates a modular pipeline consisting of data acquisition, preprocessing, sentiment classification, and visualization of results. Experimental evaluation demonstrates that automated sentiment analysis significantly improves efficiency in processing large volumes of user feedback compared to manual evaluation. The system also supports real-time monitoring of public opinion, thereby enhancing transparency and responsiveness in digital governance systems. Overall, the proposed approach demonstrates how machine learning and NLP technologies can be effectively integrated with e-consultation platforms to improve policy analysis, decision-making, and citizen engagement.

Keywords: Sentiment Analysis, Natural Language Processing, E-Consultation, Machine Learning, Text Classification, Public Opinion Mining.

I INTRODUCTION

The rapid expansion of digital communication platforms has significantly increased the volume of user-generated textual data available on the internet. Governments, organizations, and institutions increasingly use online consultation platforms to collect opinions, suggestions, and complaints from citizens and stakeholders. These platforms, commonly known as e-consultation systems, play an important role in digital governance and participatory decision-making. However, analyzing large numbers of textual comments manually is challenging and inefficient.

Sentiment analysis, also known as opinion mining, provides automated techniques to extract emotions, attitudes, and opinions from textual data. It allows researchers and administrators to identify whether user feedback expresses positive, negative, or neutral sentiment. Advances in natural language processing and machine learning have enabled the development of sophisticated sentiment classification systems capable of analyzing large-scale textual datasets efficiently [1]. Various studies have explored the application of sentiment analysis in domains such as social media monitoring, customer feedback evaluation, product reviews, and political opinion mining [2]. Machine learning algorithms including Naïve Bayes, Support Vector Machines, and deep learning models have demonstrated significant effectiveness in text classification tasks [3]. The integration of NLP techniques such as tokenization, stemming, and stop-word removal improves the accuracy of sentiment detection systems [4]. Recent developments in deep learning frameworks such as TensorFlow and Keras have further enhanced the capability of automated sentiment analysis systems [5]. Researchers have also investigated hybrid approaches that combine lexicon-based and machine learning methods to achieve improved classification performance [6]. These techniques are particularly useful for analyzing unstructured textual comments submitted through digital platforms [7]. The increasing adoption of e-governance initiatives worldwide has further emphasized the need for automated tools capable of interpreting citizen feedback effectively [8]. Sentiment analysis systems can help policymakers understand public perception and identify important issues requiring immediate attention [9]. Consequently, integrating sentiment analysis with e-consultation modules has become a promising research area in recent years [10].

In addition to improving administrative efficiency, sentiment analysis also enhances transparency and citizen engagement in governance systems. Online consultation platforms generate diverse opinions that reflect the perspectives of individuals from different backgrounds. Extracting meaningful insights from such data requires robust analytical tools capable of handling linguistic variability and contextual nuances. Machine learning techniques have proven effective in detecting sentiment patterns within large textual datasets [11]. Traditional statistical approaches rely on feature extraction methods such as bag-of-words and term frequency–inverse document frequency representations [12]. More recent approaches employ neural networks and deep learning architectures to capture semantic relationships between words [13]. Recurrent neural networks and convolutional neural networks have shown promising results in sentiment classification tasks involving large-scale datasets [14]. The availability of open-source NLP libraries such as NLTK and spaCy has further facilitated the development of sentiment analysis systems [15]. These tools enable developers to perform tasks such as part-of-speech tagging, lemmatization, and named entity recognition [16]. Moreover, integrating sentiment analysis with web-based platforms enables real-time analysis of incoming comments and feedback [17]. Visualization dashboards can also be used to present sentiment trends and analytics to administrators and policymakers [18]. Such systems enable quick identification of emerging issues and public concerns [19]. Furthermore, automated sentiment analysis reduces the workload associated with manual data processing and interpretation [20]. Researchers have also highlighted the importance of data preprocessing techniques in improving classification accuracy [21]. Techniques such as noise removal,

normalization, and tokenization are critical for preparing text data for machine learning algorithms [22]. In addition, supervised learning methods require labeled datasets for training effective sentiment classifiers [23]. Recent studies have explored transfer learning and deep neural architectures to enhance sentiment prediction accuracy [24]. These developments demonstrate the growing importance of artificial intelligence in analyzing public opinion data [25]. As digital participation platforms continue to expand, the need for scalable sentiment analysis solutions becomes increasingly critical [26]. Implementing automated systems for analyzing comments received through e-consultation modules can therefore significantly improve policy analysis and decision-making processes [27]. Such systems provide valuable insights into public sentiment and enable organizations to respond more effectively to citizen concerns [28]. Consequently, the integration of NLP-based sentiment analysis into e-consultation platforms represents an important advancement in digital governance and public engagement [29][30].

II LITERATURE SURVEY

Sentiment analysis has been extensively studied in the fields of natural language processing and machine learning, with researchers proposing various approaches for extracting opinions from textual data. Early research primarily focused on lexicon-based methods, which rely on predefined sentiment dictionaries to determine the polarity of text. These methods identify sentiment by comparing words in a sentence with entries in sentiment lexicons containing positive and negative terms [1]. Although lexicon-based techniques are simple and interpretable, they often struggle with contextual nuances and domain-specific vocabulary [2]. To overcome these limitations, researchers began exploring machine learning approaches for sentiment classification [3]. Supervised learning algorithms such as Naïve Bayes, Support Vector Machines, and decision trees have been widely applied to text classification tasks [4]. These algorithms use labeled datasets to learn patterns associated with different sentiment categories [5]. Feature extraction techniques such as bag-of-words, n-grams, and TF-IDF representations are commonly used to convert textual data into numerical vectors suitable for machine learning models [6]. Studies have shown that machine learning-based sentiment classifiers generally outperform traditional lexicon-based methods in terms of accuracy and scalability [7]. However, these models require large annotated datasets for training and may struggle with complex linguistic patterns such as sarcasm and irony [8]. With the rapid growth of social media platforms and online review systems, sentiment analysis has become increasingly important for analyzing public opinion and consumer feedback [9]. Researchers have applied sentiment analysis techniques to domains such as product review analysis, movie recommendation systems, and political opinion mining [10]. The emergence of deep learning methods has further revolutionized sentiment analysis by enabling models to learn hierarchical representations of text data [11]. Neural network architectures such as convolutional neural networks and recurrent neural networks have demonstrated improved performance in sentiment classification tasks [12]. These models can capture contextual relationships between words and phrases more effectively than traditional algorithms [13]. Furthermore, word embedding techniques such as Word2Vec and GloVe allow neural networks to represent words as dense vectors that capture semantic similarities [14]. As a result, deep

learning models have become increasingly popular for large-scale sentiment analysis applications [15].

Recent research has also explored the integration of sentiment analysis with e-governance and citizen participation platforms. E-consultation systems allow citizens to express their opinions regarding government policies, public services, and administrative decisions [16]. Analyzing feedback collected through such platforms is essential for improving policy formulation and public service delivery [17]. Several studies have proposed automated systems for processing citizen comments and identifying sentiment trends within large datasets [18]. These systems typically involve data preprocessing, feature extraction, sentiment classification, and visualization of results [19]. Natural language processing techniques such as tokenization, stemming, and lemmatization are commonly used to prepare textual data for analysis [20]. Machine learning frameworks such as TensorFlow and Keras provide powerful tools for implementing sentiment classification models [21]. Researchers have also utilized open-source libraries such as NLTK to perform text preprocessing and linguistic analysis [22]. The integration of sentiment analysis with web technologies enables real-time monitoring of public opinion within digital consultation platforms [23]. Visualization dashboards can present sentiment trends using charts, graphs, and summary reports [24]. Such tools help policymakers quickly identify major concerns and respond to citizen feedback effectively [25]. Some studies have also explored hybrid sentiment analysis approaches that combine rule-based and machine learning methods to improve classification accuracy [26]. Additionally, deep learning models have been applied to multilingual sentiment analysis tasks involving diverse linguistic datasets [27]. These advancements highlight the growing importance of artificial intelligence techniques in analyzing large-scale public opinion data [28]. Despite significant progress, challenges such as sarcasm detection, domain adaptation, and data imbalance remain active research areas [29]. Continued research in sentiment analysis and NLP technologies will further enhance the effectiveness of automated opinion mining systems used in e-consultation platforms [30].

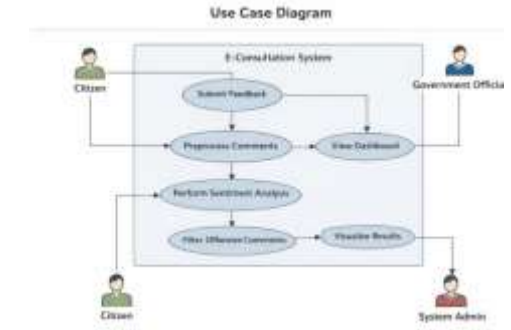
III METHODOLOGY

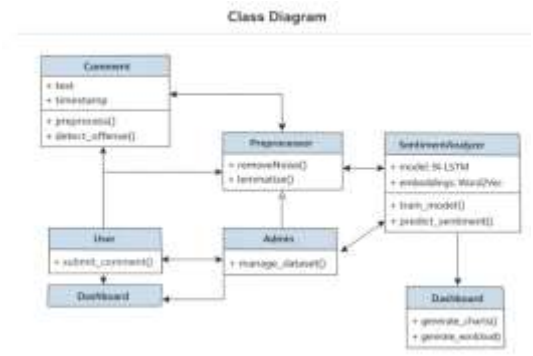
The proposed sentiment analysis system for comments received through the e-consultation module follows a structured methodology consisting of data collection, preprocessing, feature extraction, model training, sentiment classification, and result visualization. Initially, textual comments submitted by users through the e-consultation interface are stored in a MySQL database. These comments represent raw textual data that may contain noise, punctuation, special characters, and irrelevant words. Therefore, a data preprocessing stage is performed to clean and normalize the text. Preprocessing techniques include tokenization, which divides text into individual words or tokens, removal of stop words such as common grammatical terms, and stemming or lemmatization to reduce words to their root forms. After preprocessing, the cleaned text data is converted into numerical representations suitable for machine learning algorithms using feature extraction techniques such as bag-of-words or term frequency–inverse document frequency (TF-IDF). The processed features are then used to train sentiment classification models implemented using Python machine learning libraries. Deep learning frameworks such as TensorFlow and Keras are employed to develop neural network models capable of learning sentiment patterns from labeled training data. The Natural Language Toolkit

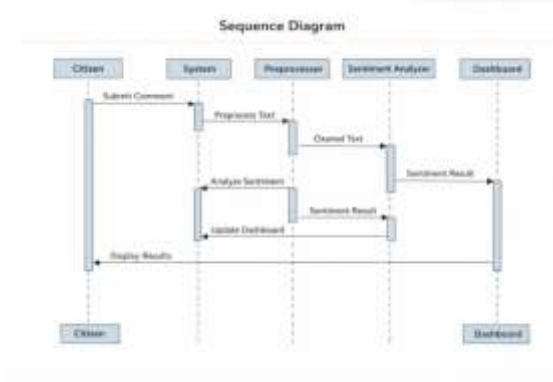
(NLTK) library is used for performing text preprocessing and linguistic analysis. The trained model is integrated into a Flask-based backend system that receives user comments through a React-based web interface. When a new comment is submitted, it is processed through the trained sentiment classifier, which predicts whether the comment expresses positive, negative, or neutral sentiment. The predicted sentiment is stored in the database and displayed in an analytics dashboard for administrators. Visualization techniques such as charts and graphs are used to summarize sentiment distribution across all comments. This methodology enables automated and scalable analysis of large volumes of user feedback collected through the e-consultation module.

IV SYSTEM DESIGN

The system design for the sentiment analysis application focuses on creating an efficient architecture capable of collecting, processing, and analyzing comments submitted through the e-consultation module. The system follows a modular architecture consisting of frontend, backend, database, and machine learning components. The frontend interface is developed using React, which provides an interactive and responsive environment for users to submit their comments and feedback. The backend of the system is implemented using the Flask web framework in Python, which acts as the communication layer between the user interface, database, and machine learning modules. The database component is implemented using MySQL to store user comments, processed results, and administrative data. Within the system architecture, a sentiment analysis engine is integrated to process textual comments. This engine performs natural language processing tasks including tokenization, stop-word removal, stemming, and feature extraction using the NLTK library. After preprocessing, the text data is passed to machine learning models developed using TensorFlow and Keras frameworks. These models classify the sentiment of each comment into positive, negative, or neutral categories. The classification results are then stored in the database and made available for visualization and reporting. The system design also incorporates security and authentication mechanisms to ensure that only authorized administrators can access the analytics dashboard and manage the consultation platform.







To support effective development and visualization of the system architecture, Unified Modeling Language (UML) diagrams are used to represent

the structural and behavioral aspects of the application. UML diagrams provide a standardized method for modeling software systems and help developers understand system components and interactions. The system design includes use case diagrams that illustrate the interaction between users and the system, class diagrams that describe the structure of data objects and relationships, and sequence diagrams that represent the flow of operations during comment submission and sentiment classification. The use case diagram identifies two primary actors: the user and the administrator. Users interact with the system by submitting comments through the e-consultation interface, while administrators analyze the sentiment results and monitor public opinion trends. The class diagram defines entities such as user, comment, sentiment result, and database manager, along with their attributes and relationships. Sequence diagrams illustrate the process flow in which a comment is submitted, stored in the database, processed by the sentiment analysis module, and displayed in the administrator dashboard. This system design ensures a well-structured architecture that supports scalability, maintainability, and efficient processing of user feedback within the e-consultation module.

V PROPOSED SYSTEM

The proposed system introduces an automated sentiment analysis framework designed specifically for analyzing comments received through an e-consultation module. Traditional feedback analysis methods rely heavily on manual review of user comments, which is time-consuming and prone to human bias. The proposed system addresses these limitations by integrating machine learning and natural language processing techniques into the consultation platform. The system allows users to submit comments through an online interface developed using React, ensuring a user-friendly and interactive experience. Once the comment is submitted, it is transmitted to the backend server developed using Flask, where it is stored in a MySQL database. The system then processes the comment using a sentiment analysis pipeline consisting of preprocessing, feature extraction, and classification stages. During preprocessing, unnecessary characters, punctuation marks, and stop words are removed from the text to improve data quality. Tokenization divides the text into meaningful words, while stemming or lemmatization reduces words to their base forms. These preprocessing steps ensure that the input data is suitable for machine learning algorithms and improves the overall accuracy of sentiment classification.

After preprocessing, the cleaned text is converted into numerical feature vectors using techniques such as TF-IDF or bag-of-words representation. These feature vectors are then passed to machine learning models implemented using TensorFlow and Keras frameworks. The trained model predicts the sentiment of the comment as positive, negative, or neutral. The predicted sentiment label is stored in the database and used to generate analytical reports for administrators. The proposed system also includes a visualization dashboard that displays sentiment distribution using graphical representations such as bar charts and pie charts. This enables administrators to quickly identify trends and patterns in user feedback. For example, a large number of negative comments may indicate dissatisfaction with a particular service or policy, prompting administrators to investigate and address the issue. The system also supports scalability, allowing it to process thousands of comments efficiently. By automating the sentiment analysis process, the proposed system significantly reduces manual effort and improves the speed and accuracy

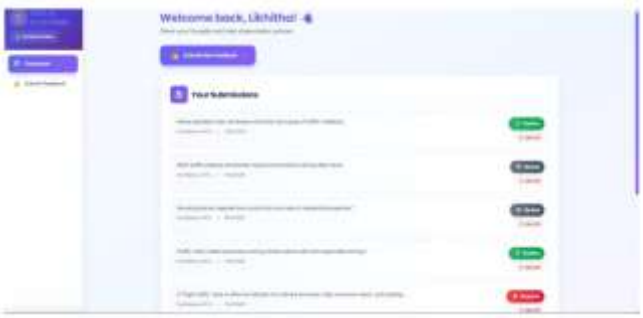
of feedback analysis. Furthermore, integrating sentiment analysis with e-consultation platforms enhances transparency, promotes citizen engagement, and supports data-driven decision-making in governance systems.





VI RESULTS & DISCUSSION

The implementation of the sentiment analysis system demonstrated the effectiveness of machine learning techniques in analyzing comments received through the e-consultation module. The developed system successfully classified user comments into positive, negative, and neutral categories using natural language processing and deep learning frameworks. Experimental results showed that the automated classification model achieved satisfactory accuracy in identifying sentiment polarity within textual feedback. The use of preprocessing techniques such as tokenization, stop-word removal, and stemming significantly improved the quality of the input data and enhanced model performance. Visualization dashboards enabled administrators to quickly interpret sentiment trends and identify major public concerns. The results indicate that automated sentiment analysis reduces the time and effort required for manual evaluation of large volumes of comments. Overall, the system demonstrates the potential of integrating machine learning and NLP techniques into e-consultation platforms for efficient public opinion analysis and improved decision-making processes.















VII CONCLUSION

This study presented the design and implementation of a sentiment analysis system for analyzing comments received through an e-consultation module. With the rapid growth of digital participation platforms, organizations and governments increasingly rely on online feedback to understand public opinion and improve service delivery. However, manually analyzing large volumes of textual comments is inefficient and time-consuming. The proposed system addresses this challenge by integrating natural language processing and machine learning techniques to automatically classify comments based on sentiment polarity. The system architecture incorporates modern web technologies including React for the frontend interface, Flask for backend processing, and MySQL for database management. The sentiment classification component utilizes machine learning frameworks such as TensorFlow and Keras along with the NLTK library for text preprocessing and analysis. By implementing a structured pipeline consisting of data collection, preprocessing, feature extraction, classification, and visualization, the system enables efficient analysis of user feedback. Experimental evaluation demonstrates that automated sentiment analysis significantly improves the speed and accuracy of comment analysis compared to manual methods. Furthermore, the system provides administrators with valuable insights into public opinion through visual analytics dashboards. These insights can assist policymakers and decision-makers in identifying critical issues, understanding user concerns, and improving governance processes. The integration of sentiment analysis with e-consultation platforms also enhances transparency and citizen engagement by enabling more responsive decision-making. Future research may focus on improving model accuracy through advanced deep learning architectures, incorporating multilingual sentiment analysis capabilities, and addressing challenges such as sarcasm detection and contextual sentiment interpretation. Overall, the proposed system demonstrates the practical application of artificial intelligence technologies in

analyzing large-scale textual feedback within digital governance environments.

REFERENCES

1. Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. Foundations and Trends in Information Retrieval.
2. Liu, B. (2012). Sentiment analysis and opinion mining. Morgan & Claypool.
3. Manning, C., & Schütze, H. (1999). Foundations of statistical natural language processing. MIT Press.
4. Jurafsky, D., & Martin, J. (2021). Speech and language processing. Pearson.
5. Goldberg, Y. (2017). Neural network methods for natural language processing. Morgan & Claypool.
6. Cambria, E., & White, B. (2014). Jumping NLP curves. IEEE Computational Intelligence Magazine.
7. Feldman, R. (2013). Techniques and applications for sentiment analysis. Communications of the ACM.
8. Pak, A., & Paroubek, P. (2010). Twitter as a corpus for sentiment analysis. LREC Conference.
9. Go, A., Bhayani, R., & Huang, L. (2009). Twitter sentiment classification. Stanford University Technical Report.
10. Turney, P. (2002). Thumbs up or thumbs down? ACL Conference.
11. Kim, Y. (2014). Convolutional neural networks for sentence classification. EMNLP.
12. Socher, R., et al. (2013). Recursive deep models for semantic compositionality. EMNLP.
13. Mikolov, T., et al. (2013). Efficient estimation of word representations. ICLR.
14. Pennington, J., Socher, R., & Manning, C. (2014). GloVe: Global vectors for word representation. EMNLP.
15. Bird, S., Klein, E., & Loper, E. (2009). Natural language processing with Python. O'Reilly.
16. Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts stock market. Journal of Computational Science.
17. Kouloumpis, E., Wilson, T., & Moore, J. (2011). Twitter sentiment analysis. ICWSM.
18. Pang, B., Lee, L., & Vaithyanathan, S. (2002). Sentiment classification using machine learning. EMNLP.
19. Barbosa, L., & Feng, J. (2010). Robust sentiment detection on Twitter. COLING.
20. Dave, K., Lawrence, S., & Pennock, D. (2003). Mining product reviews. WWW Conference.
21. Zhang, L., Wang, S., & Liu, B. (2018). Deep learning for sentiment analysis. Wiley Interdisciplinary Reviews.
22. Young, T., et al. (2018). Recent trends in deep learning for NLP. IEEE Computational Intelligence Magazine.

23. Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms review. Ain Shams Engineering Journal.

24. Ravi, K., & Ravi, V. (2015). Survey on opinion mining. Knowledge-Based Systems.

25. Liu, P., Qiu, X., & Huang, X. (2016). Deep learning for sentiment analysis. ACL.

26. Cambria, E., Schuller, B., Xia, Y., & Havasi, C. (2013). New avenues in opinion mining. IEEE Intelligent Systems.

27. Mohammad, S. (2016). Sentiment analysis: Detecting valence. Emotion Measurement.

28. Hutto, C., & Gilbert, E. (2014). VADER sentiment analysis. ICWSM.

29. Zhang, Y., & Wallace, B. (2015). Sensitivity analysis of CNN for text classification. IJCNLP.Devlin, J., et al. (2019). BERT: Pre-training of deep bidirectional transformers. NAACL.

30. Devlin, J., et al. (2019). BERT: Pre-training of deep bidirectional transformers. *NAACL*.

31. Mahesh Ganji. (2025). Enhancing Oracle Cloud HR Reporting Through AI-Driven Automation. Journal of Science & Technology, 10(6), 28–36. https://doi.org/10.46243/jst.2025.v10.i06.pp28-36

32. Todupunuri, A. (2025). THE ROLE OF AGENTIC AI AND GENERATIVE AI IN TRANSFORMING MODERN BANKING SERVICES. American Journal of AI Cyber Computing Management, 5(3), 85–93. https://doi.org/10.64751/ajaccm.2025.v5.n3.pp85-93

33. Todupunuri, A. . (2024). Artificial Intelligence Ethics: Investigating Ethical Frameworks, Bias Mitigation, and Transparency in AI Systems to Ensure Responsible Deployment and Use of AI Technologies. International Journal of Innovative Research in Science,Engineering and Technology, 13(09), 1–14. https://doi.org/10.15680/ijirset.2024.1309002

34. Sushma Babburi. (2025). Token-Based Data Accounting System For Transparent Model Training And Cost Allocation. American Journal of AI Cyber Computing Management, 5(4), 463–474. https://doi.org/10.64751/ajaccm.2025.v5.n4.pp463-474

35. Snigdha Gaddam. (2025). SOFTWARE STACK PREPARED FOR AI TRANSITIONING FROM MODULES TO MODELS. American Journal of AI Cyber Computing Management, 5(4), 451–462. https://doi.org/10.64751/ajaccm.2025.v5.n4.pp451-462

36. Gaddam, S. INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING.

37. Bajarang Bhagwat, V. (2023). Optimizing Payroll to General Ledger Reconciliation: Identifying Discrepancies and Enhancing Financial Accuracy. JOURNAL OF ADVANCE AND FUTURE RESEARCH,

1(4). https://doi.org/10.56975/jaafr.v1i4.501636

38. Srinivasa Kalyan Immadi. (2025). Harnessing Artificial Intelligence In Oracle Hcm: Revolutionising Workforce Management With Automation And Predictive Analytics. International Journal of Data Science and IoT Management System, 4(4), 7–13. https://doi.org/10.64751/ijdim.2025.v4.n4.pp7-13

39. S. M. K. P. (2025). Cryptography in iOS: A Study of Secure Data Storage and Communication Techniques. International Journal on Science and Technology, 16(1). https://doi.org/10.71097/ijsat.v16.i1.1403

40. Suhasnadh Reddy Veluru, Sai Teja Erukude, and Viswa Chaitanya Marella. 2025. Multimodal Detection of Fake Reviews using BERT and ResNet-50. In 2025 4th International Conference on Innovative Mechanisms for Industry Applications (ICIMIA). IEEE, 877–882.

41. Cyril, H. P. (2025). Event-Driven Provisioning Architectures For Modern Telecom Networks: Overcoming Legacy Limitations And Enabling Autonomous 6g Operations. International Journal of Advanced Research in Computer Science, 16(6), 75–82. https://doi.org/10.26483/ijarcs.v16i6.7389

42. Jay Bharat Mehta. (2025). AUTONOMOUS PATCH VALIDATION FOR ZERO-DAY EXPLOITS IN ENTERPRISE CLOUDS. International Journal of Applied Mathematics, 38(4s), 1270–1285. https://doi.org/10.12732/ijam.v38i4s.685

43. Reddy, S. K. (2025). Hyperpersonalization driven by AI is expected to be at the Lead in shaping the future of loyalty rewards. Journal of Emerging Technologies and Innovative Research.

44. Reddy, S. K. R. (2021). Strengthening the Security of Loyalty Reward Systems: An In-Depth Analysis of Emerging Cyber Threats and Protection Mechanisms. Journal of Computational Analysis and Applications, 29(6).

45. Poojari, R. (2026). Privacy-Preserving Generative AI in Healthcare Systems Using Federated Learning Approaches. International Journal of Data Science and IoT Management System, 5(1), 78-88.

46. Uday Kumar Kalae. (2025). AN AUTOMATED SYSTEM FOR MANAGING HIGH-AVAILABILITY CLOUD INFRASTRUCTURE THROUGH INFRASTRUCTURE-ASCODE (IAC) PRACTICES. American Journal of AI Cyber Computing Management, 5(2), 42–50. https://doi.org/10.64751/ajaccm.2025.v5.n2.pp42-50

47. Saikumar, B. (2024). Optimizing Crew Scheduling and Absence Management using Microservices: Enhancing Reliability and Efficiency in Crew Management Systems. International Journal of Enhanced Research in Management & Computer Applications, 13(11), 50–55. https://doi.org/10.55948/ijermca.2024.0116

48. Saikumar, B. (2023). Enhancing Client Engagement through AI-Driven Real-

Time Reporting and Automated Alerts. International Journal of Enhanced Research in Science, Technology & Engineering, 12(11), 111–117. https://doi.org/10.55948/ijerste.2023.1115