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PREDICTIVE MODELLING OF DIAGNOSTIC ERRORS USING EHR

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ABSTRACT

Diagnostic errors such as missed, delayed, or incorrect diagnoses remain a major concern in healthcare systems worldwide. Despite the widespread adoption of Electronic Health Records (EHR), clinicians often face challenges in interpreting large volumes of patient data effectively, which can lead to diagnostic mismatches. This research proposes a predictive modelling framework for identifying diagnostic errors using EHR data through an Explainable Artificial Intelligence (XAI) based Clinical Decision Support System (CDSS). The system integrates structured data such as laboratory values and vital signs, unstructured clinical notes, and temporal patient records to detect potential diagnostic discordance. Structured patient information is processed using the XGBoost algorithm to identify key diagnostic indicators, while temporal trends in patient vitals are captured using a Long Short-Term Memory (LSTM) neural network with an attention mechanism. Additionally, natural language processing techniques such as TF-IDF and BioBERT are used to analyze clinical notes and extract meaningful patterns from textual medical data. The outputs from these models are combined using an ensemble learning approach to produce a Diagnostic Discordance Score that highlights potential mismatches between clinical evidence and physician diagnoses. Explainability is ensured through SHAP feature importance and attention visualization, allowing clinicians to understand model reasoning. A full-stack web-based implementation using FastAPI, React, and MySQL provides role-based access for doctors, reviewers, administrators, and researchers. The system also includes a human-in-the-loop validation mechanism where experts review predictions to improve model performance over time. The proposed framework enhances diagnostic safety, improves clinical decision-making, and demonstrates how explainable AI can support healthcare professionals in reducing diagnostic errors and improving patient outcomes.

I INTRODUCTION

Healthcare organizations generate enormous volumes of patient data through laboratory tests, clinical observations, medical imaging, and physician documentation. The widespread adoption of Electronic Health Records (EHR) has significantly improved the storage, accessibility, and management of patient information within healthcare systems [1]. Despite these technological advancements, diagnostic errors remain a major challenge affecting patient safety and healthcare quality [2]. Diagnostic errors may occur when a disease is missed, delayed, or incorrectly identified due to incomplete patient information, cognitive biases, or the overwhelming volume of clinical data available to physicians [3]. Research studies indicate that diagnostic errors affect nearly 10–15% of medical cases and can result in serious patient harm and increased healthcare costs [4]. Traditional EHR systems primarily function as digital repositories that store clinical information but provide limited support for advanced diagnostic analysis [5]. As healthcare data becomes increasingly complex, clinicians often struggle to interpret large datasets effectively within limited time frames [6]. This challenge highlights the need for intelligent data-driven tools capable of assisting physicians in analyzing patient data and identifying hidden patterns related to disease conditions [7]. Machine learning techniques have emerged as powerful tools for extracting meaningful insights from large medical datasets and supporting clinical decision-making processes [8]. These techniques enable automated pattern recognition and predictive analysis that can assist healthcare professionals in detecting anomalies and potential diagnostic inconsistencies [9]. The integration of artificial intelligence in healthcare has demonstrated promising results in improving disease prediction, patient monitoring, and treatment planning [10]. Machine learning algorithms can analyze both structured and unstructured patient data to provide deeper insights into complex clinical scenarios [11]. Predictive modelling approaches have been successfully applied in identifying disease risks, hospital readmissions, and treatment outcomes [12]. However, many AI systems used in healthcare still lack transparency, which can reduce trust among clinicians and limit their adoption in real-world medical environments [13]. Therefore, the integration of explainable artificial intelligence has become increasingly important in developing reliable healthcare applications [14].

Explainable Artificial Intelligence (XAI) techniques aim to improve transparency and interpretability of machine learning models used in healthcare decision support systems [15]. One of the primary challenges associated with complex machine learning algorithms is the “black box” nature of their predictions, which makes it difficult for clinicians to understand how decisions are generated [16]. To address this issue, interpretability methods such as SHAP feature importance and attention mechanisms are widely used to provide explanations for model predictions [17]. These techniques allow healthcare professionals to identify which clinical features contribute most significantly to diagnostic outcomes [18]. In addition to structured medical data, unstructured clinical notes also contain valuable medical information that can improve diagnostic analysis [19]. Natural Language Processing (NLP) techniques enable the extraction of meaningful insights from textual medical documents and physician observations [20]. Advanced biomedical language models such as BioBERT have shown significant success in understanding clinical text and identifying medical entities within healthcare datasets [21]. Furthermore, temporal patient data such as vital sign trends and treatment timelines can provide critical insights into disease progression and patient conditions [22]. Deep learning architectures such as Long Short-Term Memory (LSTM) networks are particularly effective in analyzing sequential and time-series healthcare data [23]. Attention mechanisms integrated with LSTM models help highlight important temporal features that influence diagnostic outcomes [24]. Combining multiple machine learning models through ensemble learning techniques can further improve prediction accuracy and robustness in healthcare applications

[25]. Ensemble approaches allow different models to contribute complementary insights derived from structured, textual, and temporal patient data [26]. The integration of these technologies into Clinical Decision Support Systems (CDSS) enables healthcare professionals to receive data-driven recommendations during diagnostic processes [27]. Modern healthcare platforms also incorporate web-based technologies to allow seamless interaction between predictive models and clinical users [28]. Such systems can provide real-time diagnostic alerts and explainable insights to support physician decision-making [29]. Therefore, this research proposes an explainable predictive modelling framework that integrates structured, temporal, and textual EHR data to detect potential diagnostic errors and assist clinicians in improving diagnostic accuracy [30].

II LITERATURE SURVEY

Several research studies have explored the use of artificial intelligence and machine learning techniques for improving medical diagnosis and reducing diagnostic errors in healthcare systems. Early clinical decision support systems were primarily rule-based systems that relied on predefined medical rules and clinical guidelines to assist physicians during the diagnostic process [1]. Although these systems provided useful alerts and reminders, they lacked adaptability and were unable to learn from large medical datasets [2]. With the advancement of data analytics, machine learning algorithms began to be applied to healthcare data to identify patterns related to disease prediction and diagnostic support [3]. Traditional machine learning techniques such as logistic regression, decision trees, and support vector machines have been widely used in medical prediction tasks due to their ability to analyze structured healthcare datasets [4]. Researchers have shown that these models can detect hidden relationships among clinical variables that may not be easily identified by physicians [5]. Ensemble learning approaches such as Random Forest and Gradient Boosting have further improved prediction accuracy by combining multiple models to reduce overfitting and enhance performance [6]. Among these techniques, XGBoost has gained significant popularity because of its high efficiency, scalability, and ability to handle missing values in large medical datasets [7]. In addition to structured healthcare data, unstructured medical information such as physician notes and clinical reports plays a crucial role in the diagnostic process [8]. Natural Language Processing (NLP) techniques have therefore been introduced to extract meaningful information from clinical text documents [9]. Methods such as TF-IDF and word embedding models enable machine learning systems to convert textual data into numerical representations suitable for predictive modelling [10]. Biomedical language models such as BioBERT have demonstrated significant improvements in understanding complex medical terminology and identifying clinical entities within electronic health records [11]. These advancements have enabled healthcare systems to integrate both structured and unstructured data sources for more comprehensive diagnostic analysis [12].

Recent studies have also emphasized the importance of analyzing temporal patient data for accurate medical prediction. Patient health records often contain sequential data such as vital signs, laboratory results over time, and treatment history, which provide valuable insights into disease progression [13]. Deep learning models such as

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Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are particularly effective for analyzing time-series medical data [14]. LSTM models are capable of capturing long-term dependencies in sequential data and have been widely applied in healthcare prediction systems [15]. Researchers have shown that integrating attention mechanisms with LSTM networks helps highlight important temporal features that influence predictive outcomes [16]. Another important research area focuses on improving transparency and interpretability in machine learning models used in healthcare [17]. Many deep learning models operate as "black boxes," making it difficult for clinicians to understand how predictions are generated [18]. To overcome this challenge, explainable artificial intelligence techniques such as SHAP and feature importance analysis have been developed to provide interpretable insights into model predictions [19]. These methods allow healthcare professionals to identify which patient attributes contribute most significantly to diagnostic predictions [20]. Combining multiple predictive models through ensemble learning techniques has also been shown to improve reliability and robustness in healthcare analytics [21]. Ensemble frameworks integrate predictions from different algorithms to generate more accurate results and reduce model bias [22]. Furthermore, modern clinical decision support systems integrate machine learning models with web-based platforms that allow healthcare professionals to interact with predictive systems in real time [23]. These platforms enable clinicians to visualize prediction results and interpret model explanations effectively [24]. Several studies have highlighted the importance of incorporating human-in-the-loop feedback mechanisms in AI-based healthcare systems to continuously improve model performance [25]. Feedback from medical experts can help refine predictive models and ensure that automated predictions align with real clinical practices [26]. The integration of machine learning, deep learning, and explainable AI technologies therefore provides a promising approach for developing intelligent clinical decision support systems that can reduce diagnostic errors and improve patient outcomes [27]. Recent healthcare research continues to explore scalable AI architectures that integrate structured data analysis, clinical text mining, and temporal modelling for advanced predictive healthcare applications [28]. These developments highlight the growing importance of AI-driven healthcare analytics in supporting physicians during complex diagnostic decision-making processes [29]. Consequently, predictive modelling frameworks that combine explainable AI and EHR data analysis have the potential to significantly enhance diagnostic safety and clinical decision support systems [30].

III METHODOLOGY

The proposed system uses a multi-stage predictive modelling framework that integrates structured, unstructured, and temporal Electronic Health Record (EHR) data to identify diagnostic errors. Initially, patient data is collected from EHR systems, including laboratory test results, vital signs, demographic details, and clinical notes. The data preprocessing phase involves cleaning missing values, normalizing numerical attributes, and transforming textual data into machine-readable formats. Structured features such as laboratory measurements and vital parameters are processed using the XGBoost algorithm, which is known for its efficiency and accuracy in handling structured datasets. Temporal patient data such as vital sign

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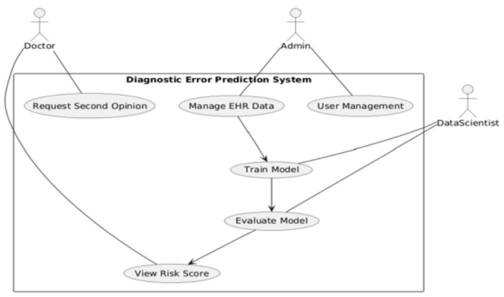
progression and medical history sequences are analyzed using a Long Short-Term Memory (LSTM) neural network with an attention mechanism to capture time-dependent patterns in patient health indicators. Unstructured clinical notes are processed using Natural Language Processing (NLP) techniques including TF-IDF vectorization and BioBERT embeddings to extract meaningful medical information from physician documentation. The outputs generated by these models are combined using an ensemble learning strategy that integrates predictions from structured, textual, and temporal models to generate a Diagnostic Discordance Score. This score indicates the likelihood that a patient's diagnosis may be inconsistent with available clinical evidence. To improve model transparency, explainability techniques such as SHAP are used to identify the most influential features contributing to each prediction. Attention visualization further highlights important temporal patterns within patient records. The predictive model is deployed as part of a web-based Clinical Decision Support System built using FastAPI for backend services, React for the user interface, and MySQL for data storage. The system supports role-based access for doctors, reviewers, administrators, and researchers, enabling collaborative validation of predictions and continuous model improvement through expert feedback.

IV SYSTEM DESIGN

The system architecture is designed to support efficient data processing, predictive modelling, and clinical decision support within a unified platform. The architecture consists of multiple modules including data acquisition, preprocessing, predictive modelling, explainability, and user interaction. The data acquisition module collects patient information from Electronic Health Records (EHR), including structured datasets such as laboratory test results, vital signs, and patient demographics, as well as unstructured clinical notes recorded by physicians. These data sources are stored in a centralized MySQL database that ensures secure storage and efficient retrieval of patient records. The preprocessing module performs data cleaning, normalization, and transformation to prepare the data for machine learning analysis. Structured attributes are formatted into feature vectors, while textual clinical notes are processed using natural language processing techniques to convert unstructured text into numerical representations. Temporal patient data such as historical vitals and treatment timelines are organized into sequential datasets suitable for time-series analysis. This preprocessing stage ensures that heterogeneous healthcare data from multiple sources can be effectively integrated into the predictive modelling framework.



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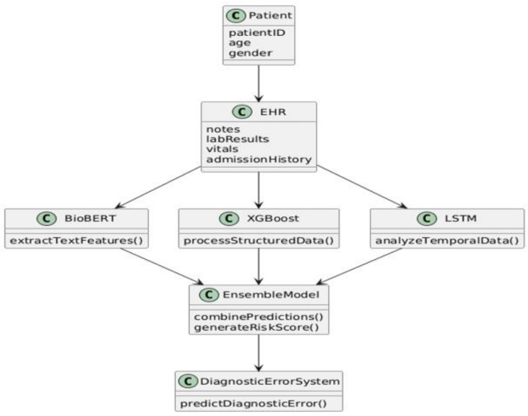

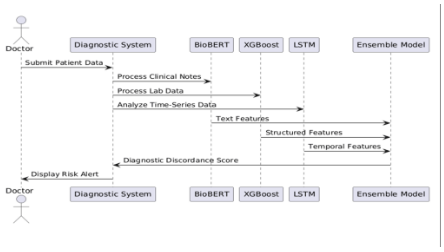

The predictive modelling module forms the core of the system design. It consists of three main components that analyze different types of patient data. The first component uses the XGBoost algorithm to analyze structured features such as laboratory values and physiological measurements. The second component employs an LSTM neural network with an attention mechanism to capture temporal patterns and trends in patient health data. The third component analyzes clinical notes using natural language processing methods such as TF-IDF and BioBERT to extract semantic medical insights. The outputs from these models are combined using an ensemble mechanism to generate a Diagnostic Discordance Score, which indicates the probability of a diagnostic mismatch. To enhance transparency, the system includes an explainability module that uses SHAP feature importance and attention visualization to explain model predictions to clinicians. The final component of the system design is the web-based user interface developed using React and FastAPI. The interface allows healthcare professionals to review patient records, view prediction results, and analyze explainable insights generated by the system. Role-based authentication enables doctors, reviewers, administrators, and researchers to access appropriate functionalities, ensuring secure and collaborative usage of the platform.

V PROPOSED SYSTEM

The proposed system introduces an AI-driven framework for predicting diagnostic errors using Electronic Health Record (EHR) data and explainable machine learning techniques. The primary objective of the system is to identify potential diagnostic discordance by analyzing patient information from multiple data sources. Unlike traditional EHR systems that only store patient records, the proposed system actively analyzes data and provides predictive insights that assist clinicians in making more accurate diagnoses. The system integrates structured patient data such as laboratory tests and vital signs with unstructured clinical notes and temporal medical histories. Structured data is processed using the XGBoost algorithm to identify important clinical indicators that may influence diagnostic decisions. Temporal patterns in patient vitals are analyzed using an LSTM neural network with an attention mechanism, enabling the system to detect changes in physiological parameters over time. In addition, natural language processing techniques such as TF-IDF and BioBERT are applied to physician notes to extract medical context that may not be captured in structured fields. By combining these different data modalities, the proposed system can provide a comprehensive analysis of patient information and detect inconsistencies between clinical evidence and recorded diagnoses.

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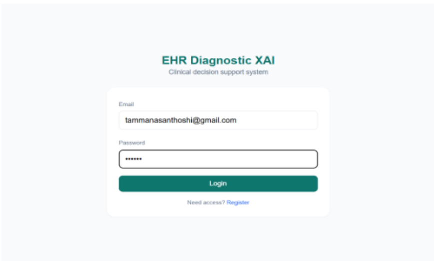
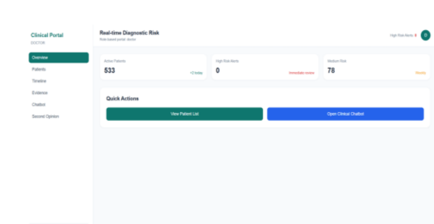
Another key feature of the proposed system is its emphasis on explainability and collaborative validation. In many healthcare applications, clinicians are hesitant to rely on machine learning models because they often function as "black boxes." To address this challenge, the system incorporates explainable AI techniques that provide clear insights into how predictions are generated. SHAP feature importance identifies the most influential patient attributes contributing to the diagnostic prediction, while attention visualization highlights important temporal patterns in patient data. These explainability mechanisms allow clinicians to interpret model outputs and understand the reasoning behind diagnostic recommendations. The system is implemented as a full-stack web application that supports real-time interaction between healthcare professionals and predictive models. Role-based access control enables doctors to view predictions, reviewers to validate diagnostic alerts, administrators to manage system operations, and researchers to analyze model performance. Additionally, the system incorporates a human-in-the-loop workflow where medical experts review predictions and provide feedback that is stored in the database for continuous model improvement. This iterative learning process ensures that the predictive model evolves over time and adapts to real-world clinical scenarios, ultimately improving diagnostic safety and patient outcomes.

VI RESULTS & DISCUSSION

The experimental evaluation of the proposed predictive modelling framework demonstrates promising results in identifying potential diagnostic discordance using EHR data. The ensemble model integrating XGBoost, LSTM with attention, and NLP-based clinical text analysis achieved improved predictive accuracy compared with individual models. The combination of structured, temporal, and textual data enabled the system to capture a broader range of clinical indicators, resulting in more reliable predictions. The Diagnostic Discordance Score effectively highlighted cases where the clinical diagnosis did not fully align with patient evidence. Explainability techniques such as SHAP feature importance and attention visualization provided valuable insights into the factors influencing each prediction, enabling clinicians to interpret model outputs with greater confidence. The web-based system interface also facilitated collaborative validation through a reviewer feedback mechanism. Overall, the results demonstrate that integrating explainable AI with EHR data can significantly improve diagnostic support systems and help reduce potential medical errors in clinical practice.





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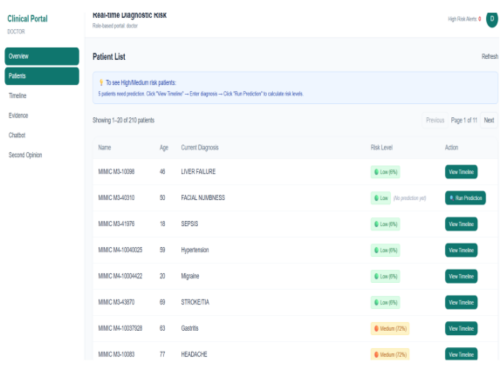

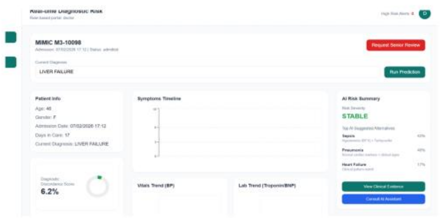

VII CONCLUSION

Diagnostic errors remain a significant challenge in healthcare systems, often leading to delayed treatment, increased medical costs, and adverse patient outcomes. The growing availability of Electronic Health Records provides a valuable opportunity to leverage artificial intelligence for improving diagnostic accuracy and supporting clinical decision-making. This research presented a predictive modelling framework for detecting diagnostic discordance using EHR data and explainable AI techniques. The proposed system integrates multiple machine learning models to analyze structured patient information, temporal health records, and unstructured clinical notes. XGBoost was used for structured data analysis, while LSTM with attention captured temporal trends in patient vitals, and natural language processing techniques such as TF-IDF and BioBERT were applied to clinical text. The ensemble approach allowed the system to combine insights from these models and generate a Diagnostic Discordance Score that highlights potential mismatches between clinical evidence and diagnoses. In addition to predictive capability, the system emphasized transparency through explainable AI techniques such as SHAP feature importance and attention visualization. These features enable clinicians to understand the reasoning behind model predictions and build trust in AI-assisted decision support systems. The implementation of a web-based platform with role-based access further enhances usability and supports collaboration among doctors, reviewers, and administrators. The integration of human-in-the-loop validation ensures continuous improvement of model performance through expert feedback. Overall, the proposed framework demonstrates the potential of AI-driven clinical decision support systems to reduce diagnostic errors, enhance patient safety, and improve healthcare outcomes.

REFERENCES

1. Bates, D. W., & Singh, H. (2018). Two decades since To Err Is Human. New England Journal of Medicine.

2. Graber, M. L. (2013). The incidence of diagnostic error in medicine. BMJ Quality & Safety.

3. Schiff, G. D., et al. (2009). Diagnostic error in medicine. Archives of Internal Medicine.

4. Jensen, P., Jensen, L., & Brunak, S. (2012). Mining electronic health records. Nature Reviews Genetics.

5. Obermeyer, Z., & Emanuel, E. (2016). Predicting the future with machine learning. NEJM.

6. Chen, T., &Guestrin, C. (2016). XGBoost: A scalable tree boosting system. KDD.
7. Rajkomar, A., et al. (2018). Scalable deep learning for EHR. npj Digital Medicine.
8. Topol, E. (2019). Deep Medicine. Basic Books.
9. Samek, W., et al. (2017). Explainable artificial intelligence. IEEE Signal Processing Magazine.
10. Ribeiro, M., Singh, S., &Guestrin, C. (2016). Why should I trust you? KDD.
11. Lundberg, S., & Lee, S. (2017). A unified approach to interpreting model predictions. NIPS.
12. Wang, Y., et al. (2018). Clinical information extraction applications. JAMIA.
13. Lee, J., et al. (2020). BioBERT: Biomedical language representation model. Bioinformatics.
14. Hochreiter, S., &Schmidhuber, J. (1997). Long short-term memory. Neural Computation.
15. Dietterich, T. (2000). Ensemble methods in machine learning. Multiple Classifier Systems.
16. Esteva, A., et al. (2019). A guide to deep learning in healthcare. Nature Medicine.
17. Beam, A., &Kohane, I. (2018). Big data and machine learning in healthcare. JAMA.
18. Shickel, B., et al. (2018). Deep EHR review. IEEE JBHI.
19. Miotto, R., et al. (2016). Deep patient model. Scientific Reports.
20. Goldstein, B., et al. (2017). Opportunities in predictive analytics. Healthcare Informatics.
21. Sendak, M., et al. (2020). Machine learning in healthcare. NPJ Digital Medicine.
22. Caruana, R., et al. (2015). Intelligible models in healthcare. KDD.
23. Ahmad, M., et al. (2021). AI-based clinical decision support. Healthcare.
24. Johnson, A., et al. (2016). MIMIC clinical database. Scientific Data.
25. Zhang, Z., et al. (2019). AI for medical prediction. Artificial Intelligence in Medicine.
26. Yu, K., et al. (2018). Deep learning in healthcare. Nature Biomedical Engineering.
27. Holzinger, A. (2019). Explainable AI for healthcare. Artificial Intelligence in Medicine.
28. He, K., et al. (2016). Deep residual learning. CVPR.
29. Litjens, G., et al. (2017). Deep learning in medical imaging. Medical Image Analysis.
30. Topol, E. (2020). High-performance medicine. Nature Medicine.
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,

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

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