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

REAL-TIME INSURANCE RISK PREDICATION WITH CONTINUOUS LEARNING AND EXPLAINABLE AI

[1]Md.AHMED,[2]KUMBHAM SAI NAGA RAJU,[3]RAJULAPATI YASWANTH, [4]KALLAGUNTA HEMANTH SAI PRAVEEN, [5]JALDULA PRAVEEN KUMAR

[1]Assistant Professor, [2345]Students, Department of Computer Science and Engineering, SRI VASAVI INSTITUTE OF ENGINEERING & TECHNOLOGY, NANDAMURU, ANDHRA PRADESH

ABSTRACT

Insurance underwriting requires accurate and timely assessment of risk to ensure fair premium pricing and sustainable operations for insurance providers. Traditional actuarial models primarily rely on static demographic tables and historical averages, which often fail to capture complex behavioural patterns and nonlinear relationships present in modern healthcare and lifestyle data. To address these limitations, this study proposes AIRIS-X (Autonomous Insurance Risk Intelligence System), a real-time insurance risk prediction framework that integrates machine learning, continuous learning mechanisms, and explainable artificial intelligence. The system collects policyholder data including age, gender, body mass index, number of children, smoking habits, geographic region, pre-existing medical conditions, preferred hospital networks, and co-payment preferences. Using these inputs, a trained XGBoost classifier predicts the probability of insurance risk and categorizes users into low, medium, or high-risk groups. The system addresses dataset imbalance using the Synthetic Minority Oversampling Technique (SMOTE), improving model performance and fairness. Predictions are stored in a centralized database and appended to a continuously growing dataset that allows administrators to retrain the model periodically, enabling adaptive learning from new user inputs. To enhance transparency, SHAP (SHapley Additive exPlanations) is integrated to provide feature-level explanations for each prediction, allowing both insurers and users to understand key risk factors. Additionally, a rule-based recommendation module suggests suitable insurance policies and preventive health measures. A chatbot interface provides contextual assistance and answers user queries related to insurance risk factors. The proposed platform demonstrates an end-to-end intelligent insurance analytics solution that combines predictive modelling, explainability, and continuous data-driven improvement to support modern insurance decision-making systems.

Keywords: Insurance Risk Prediction, Machine Learning, Explainable AI, XGBoost, Continuous Learning, SHAP, Health Insurance Analytics.

I INTRODUCTION

The insurance industry relies heavily on accurate risk assessment to determine appropriate premium levels and maintain financial stability. Traditionally, actuarial risk assessment models have used statistical tables and historical demographic data to evaluate the probability of claims and losses. While these methods have been effective for decades, the increasing complexity of health data, lifestyle variations, and demographic diversity has exposed limitations in traditional actuarial techniques. Static models often fail to capture nonlinear relationships and dynamic behavioural patterns present in modern datasets. With the rapid growth of digital healthcare records, wearable health devices, and online insurance services, insurers now have access to large volumes of data that can potentially improve risk prediction accuracy. Machine learning techniques have therefore emerged as powerful tools capable of identifying hidden patterns and complex correlations within large datasets, enabling more accurate predictive modelling for insurance underwriting and pricing strategies [1]. Recent advancements in predictive analytics have further demonstrated the potential of artificial intelligence in transforming insurance operations by enabling automated decision-making, improved fraud detection, and personalized insurance services [2]. Machine learning algorithms such as decision trees, random forests, and gradient boosting models have been successfully applied to risk prediction tasks due to their ability to model nonlinear relationships and handle heterogeneous datasets [3]. The use of big data analytics has also enabled insurers to incorporate lifestyle factors, medical histories, and behavioural indicators into risk models [4]. However, despite these technological advancements, several challenges remain, including model interpretability, data imbalance, and the need for continuous adaptation to evolving datasets [5]. Many existing predictive systems operate as static models that are trained once and deployed without regular updates, resulting in performance degradation over time as new patterns emerge in incoming data [6]. Additionally, the lack of transparency in many machine learning models has raised concerns among regulators and stakeholders regarding the fairness and accountability of automated decision systems [7]. Explainable AI techniques have therefore become increasingly important in the insurance sector to ensure that predictions can be interpreted and justified by both analysts and customers [8]. The integration of explainability tools such as SHAP and LIME has significantly improved the interpretability of complex machine learning models [9]. These approaches allow stakeholders to understand which features influence risk predictions and how different variables contribute to the final decision [10]. As digital transformation continues to reshape financial services, insurance organizations are exploring advanced analytics platforms that combine predictive modelling, data visualization, and intelligent automation [11]. The development of real-time predictive systems has also enabled insurers to provide faster services and personalized policy recommendations to customers [12]. Furthermore, web-based platforms and cloud technologies have facilitated scalable deployment of machine learning models in insurance applications [13]. Continuous learning mechanisms are also gaining attention as they enable predictive models to update themselves using newly collected data without requiring complete system redevelopment [14]. Such adaptive systems ensure that predictive accuracy improves over time as more data becomes available [15].

In response to these challenges and opportunities, this research proposes a real-time insurance risk prediction framework that integrates machine learning, continuous learning, and explainable artificial intelligence. The proposed system, AIRIS-X, is designed to support intelligent insurance analytics by providing accurate risk predictions and interpretable insights for both insurers and policyholders. The system collects relevant user data such as demographic characteristics, lifestyle indicators, and medical conditions, which are then processed by a machine learning pipeline to generate risk predictions [16]. Advanced gradient boosting algorithms such as XGBoost have been widely recognized for their high predictive performance in classification problems involving structured data [17]. These models can effectively handle feature interactions and nonlinear relationships, making them suitable for insurance risk analysis [18]. To address the common issue of class imbalance in insurance datasets, oversampling techniques such as SMOTE are often used to generate synthetic samples of minority classes [19]. This improves model fairness and prevents bias toward majority classes during training [20]. Another critical aspect of modern predictive systems is model transparency, which is achieved in this study through SHAP-based explainability techniques that quantify the contribution of each feature to a prediction [21]. By providing clear explanations for risk predictions, the system promotes trust and accountability in automated insurance decision processes [22]. The proposed platform also includes a continuous learning mechanism that periodically retrains the predictive model using newly collected user data [23]. This allows the system to adapt to evolving health patterns, demographic changes, and emerging risk factors [24]. In addition to prediction and explanation capabilities, the system provides policy recommendations based on rule-based logic aligned with common insurance practices [25]. A chatbot interface is also integrated to assist users by answering questions related to insurance risk factors and preventive health measures [26]. The backend infrastructure is implemented using modern web technologies and scalable APIs to ensure efficient data processing and secure user authentication [27]. Visualization dashboards allow users and administrators to interpret predictions and monitor system performance in real time [28]. By combining predictive modelling, explainable AI, and continuous learning, the proposed system aims to improve the efficiency and transparency of insurance risk assessment [29]. Ultimately, this research contributes to the development of intelligent insurance analytics platforms capable of supporting data-driven decision making in modern insurance ecosystems [30].

II LITERATURE SURVEY

The application of machine learning in insurance analytics has received significant attention in recent years due to its potential to improve risk prediction accuracy and automate underwriting processes. Early studies in insurance analytics focused primarily on statistical regression models and actuarial techniques that relied on limited demographic variables [1]. While these models provided baseline predictions, they often struggled to capture complex nonlinear relationships between policyholder characteristics and claim probabilities [2]. With the advancement of data mining techniques, researchers began exploring classification algorithms such as decision trees, support vector machines, and neural networks for insurance risk prediction tasks [3]. Decision tree-based models gained popularity due to their interpretability and ability to handle categorical variables effectively [4]. Random forest algorithms further improved predictive accuracy by combining multiple decision trees and reducing model variance [5]. Gradient boosting techniques later emerged as powerful predictive models capable of achieving superior performance in structured datasets [6]. Among these methods, XGBoost has demonstrated exceptional performance in classification and regression tasks across various domains including healthcare analytics and insurance risk modelling [7]. Studies have shown that gradient boosting algorithms outperform traditional models in predicting insurance claims and identifying high-risk policyholders [8]. Despite their predictive strength, many machine learning models suffer from interpretability challenges, making it difficult for stakeholders to understand the reasoning behind predictions [9]. Explainable AI techniques have therefore been introduced to address this limitation by providing insights into model decisions [10]. Methods such as SHAP and LIME allow analysts to visualize feature contributions and explain the impact of individual variables on predictions [11]. These tools have become essential in regulated industries such as insurance and finance where transparency and fairness are critical requirements [12]. Another challenge frequently encountered in insurance datasets is class imbalance, where high-risk cases represent only a small portion of the data [13]. This imbalance can lead to biased predictions if not properly handled during model training [14]. Techniques such as oversampling, undersampling, and synthetic data generation have been proposed to address this issue [15]. Among these approaches, the Synthetic Minority Oversampling Technique (SMOTE) has proven particularly effective in generating realistic synthetic samples for minority classes [16].

In addition to predictive modelling, recent research has emphasized the importance of integrating intelligent decision support systems within insurance platforms. Web-based analytics systems have enabled insurers to process customer data in real time and generate risk predictions during policy applications [17]. These platforms often incorporate visualization dashboards that allow analysts to monitor prediction results and model performance metrics [18]. Cloud computing technologies have also enabled scalable deployment of machine learning models for large-scale insurance analytics applications [19]. Another important research direction involves the development of adaptive predictive systems capable of learning from new data continuously [20]. Continuous learning frameworks allow models to update themselves periodically without requiring complete retraining from scratch [21]. This approach ensures that predictive models remain relevant even as customer behaviour and healthcare trends evolve over time [22]. Researchers have also explored the integration of conversational agents and chatbots in insurance platforms to enhance user interaction and provide automated assistance [23]. These systems use natural language processing techniques to answer user queries and provide guidance on insurance policies and health risk factors [24]. Rule-based recommendation systems have also been implemented to suggest suitable insurance policies based on predicted risk levels and user preferences [25]. Such recommendation systems improve customer engagement by offering personalized policy options aligned with user profiles [26]. Furthermore, security mechanisms such as authentication protocols and encrypted data storage are essential for protecting sensitive health and financial information in insurance platforms [27]. Modern frameworks such as FastAPI and RESTful APIs have enabled efficient communication between machine learning models and web applications [28]. Frontend technologies such as React and data visualization libraries have also improved the usability and accessibility of predictive analytics systems [29]. Overall, the integration of machine learning, explainable AI, and modern web technologies has paved the way for advanced insurance analytics platforms capable of supporting intelligent and transparent decision-making processes [30].

III METHODOLOGY

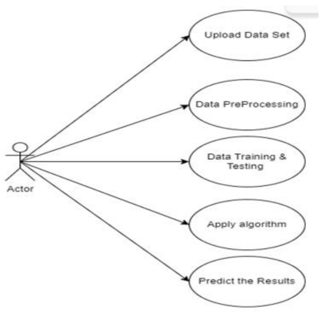
The proposed AIRIS-X system follows a machine learning–driven methodology for real-time insurance risk prediction. The process begins with data collection and preprocessing, where user-provided inputs such as age, gender, body mass index, number of children, smoking status, geographic region, presence of pre-existing diseases, preferred hospital networks, and co-payment preferences are collected through a web interface. These inputs are validated and stored in a structured database before being passed to the machine learning pipeline for processing. Data preprocessing includes cleaning missing values, encoding categorical variables, and normalizing numerical features to ensure compatibility with the machine learning model. Since insurance datasets often exhibit class imbalance between low-risk and high-risk policyholders, the Synthetic Minority Oversampling Technique (SMOTE) is applied to generate synthetic samples of minority classes and improve model training balance. After preprocessing, the dataset is split into training and testing sets to evaluate predictive performance. The core prediction engine uses the Extreme Gradient Boosting (XGBoost) algorithm, a powerful ensemble learning method known for its ability to handle complex nonlinear relationships and interactions between features. The trained model predicts a risk score and categorizes users into low, medium, or high-risk groups. Model performance is evaluated using metrics such as accuracy, ROC-AUC score, precision, recall, and F1 score to ensure reliability and predictive strength. To enhance interpretability, SHAP (SHapley Additive exPlanations) is integrated to provide feature-level explanations for each prediction, allowing users and administrators to understand the influence of individual variables on the risk score. The system also implements a continuous learning mechanism in which new user data and prediction results are appended to a centralized dataset stored in a database. Administrators can periodically trigger retraining of the model using this updated dataset, ensuring that the system adapts to evolving data patterns and improves predictive accuracy over time. The entire system is deployed as a web-based platform integrating backend APIs, a machine learning pipeline, and an interactive frontend dashboard.

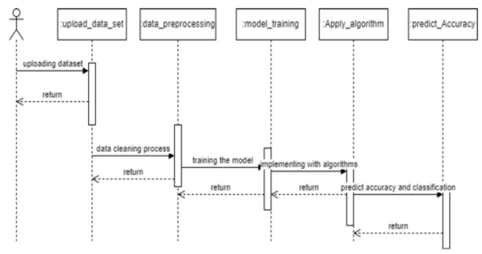
IV SYSTEM DESIGN

The AIRIS-X system is designed as a modular web-based architecture that integrates machine learning, data management, and interactive user interfaces to support real-time insurance risk prediction. The system architecture consists of three primary layers: the frontend interface, the backend server, and the machine learning analytics module. The frontend interface is developed using React and Vite, providing a responsive and interactive environment for users to submit their health and demographic information. Tailwind CSS is used to create a clean and user-friendly interface, while Recharts is integrated to visualize prediction outcomes and risk analytics through graphs and dashboards. The user interface includes modules for data input, prediction results, policy recommendations, chatbot interaction, and explanation visualization. Users can enter personal health and lifestyle information through secure forms, after which the system processes the inputs

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

and generates a risk prediction. Visualization dashboards display the predicted risk category and relevant feature contributions, helping users understand the factors influencing their risk level. Additionally, the interface allows users to view recommended insurance policies and relevant health guidance based on their predicted risk category. The frontend communicates with the backend using RESTful APIs to ensure seamless data exchange and system responsiveness.





The backend architecture is implemented using Python with the FastAPI framework, which provides high-performance API endpoints for handling data processing and machine learning inference. The backend manages user authentication, data storage, prediction requests, and model retraining operations. Security is ensured through JSON Web Token (JWT) authentication and bcrypt password hashing to protect user credentials and sensitive information. All user inputs and prediction outputs are stored in a MySQL database, which acts as the central data repository for the system. The machine learning pipeline is integrated within the backend and uses Python libraries such as Pandas and NumPy for data processing, scikit-learn for model evaluation, and XGBoost for predictive modelling. Imbalanced-learn is used to implement SMOTE for handling class imbalance, while SHAP is used to generate explanation values for model predictions. When a user submits data, the backend processes the request, sends the input features to the trained model, and returns the predicted risk category along with SHAP-based explanations. The system also maintains a continuously updated dataset by appending new user records to a central CSV file and database table. Administrators have access to a retraining module that allows the machine learning model to be updated periodically using newly collected data. This modular design ensures scalability, maintainability, and efficient real-time prediction capabilities for insurance risk assessment.

V PROPOSED SYSTEM

The proposed AIRIS-X system introduces an intelligent framework for real-time insurance risk prediction by combining machine learning, explainable artificial intelligence, and continuous learning capabilities. The primary objective of the system is to improve the accuracy, transparency, and adaptability of insurance risk assessment processes. Unlike traditional actuarial models that rely on static statistical tables, the proposed system uses dynamic machine learning algorithms capable of identifying complex relationships between health indicators and insurance risk. The system collects user information through an online interface, including demographic data, lifestyle habits, and medical history. These inputs are processed using a trained XGBoost classifier that predicts the probability of insurance risk and

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

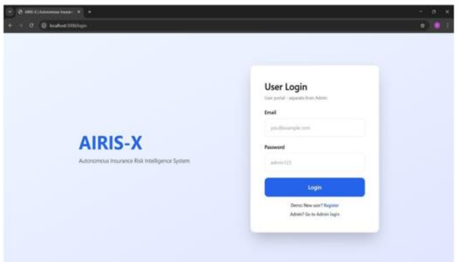
categorizes users into predefined risk levels such as low, medium, and high. The model is trained using historical insurance datasets and optimized to ensure high predictive performance. One of the key innovations of the proposed system is the integration of explainable AI techniques to improve model transparency. By incorporating SHAP-based explanation methods, the system provides feature-level insights that explain how each input variable contributes to the final risk prediction. This allows both insurance providers and policyholders to understand the reasoning behind the prediction results. Such transparency is essential for building trust in automated decision systems and ensuring compliance with regulatory requirements in the insurance industry.

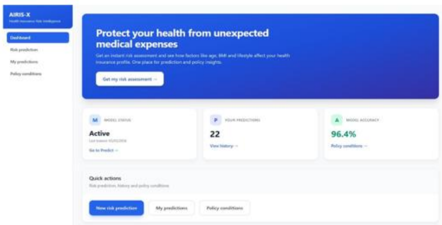
Another important feature of the proposed system is its continuous learning capability, which allows the predictive model to evolve over time as new data becomes available. Each user interaction with the system generates additional data that is stored in a centralized database and appended to a growing dataset used for model training. Administrators can periodically retrain the model using this updated dataset, enabling the system to learn from recent trends and improve prediction accuracy. This adaptive learning approach ensures that the system remains relevant even as healthcare patterns, demographic characteristics, and insurance policies change. The proposed platform also integrates a rule-based recommendation module that suggests suitable insurance policies based on the predicted risk category. For example, users identified as high-risk may receive recommendations for policies with higher coverage or preventive healthcare plans. Additionally, the system includes an interactive chatbot that provides contextual assistance and answers user questions regarding risk factors, policy conditions, and health improvement strategies. Visualization dashboards present risk analytics and feature importance in an intuitive format, enabling users to interpret predictions easily. By integrating predictive modelling, explainability, continuous learning, and user-friendly interfaces, the proposed AIRIS-X system provides a comprehensive solution for intelligent insurance risk management.

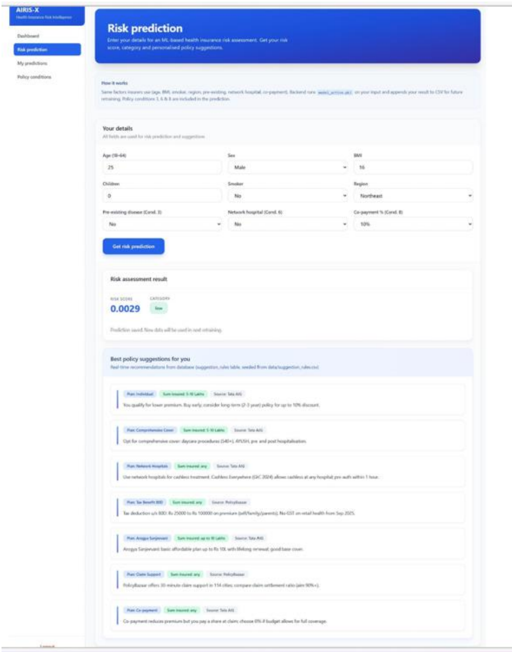
VI RESULTS & DISCUSSION

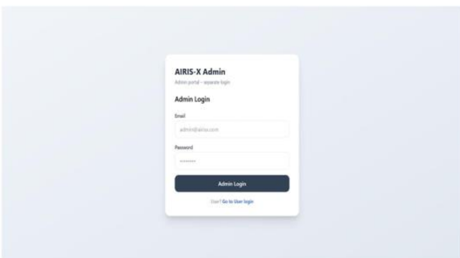
The experimental evaluation of the AIRIS-X system demonstrates its effectiveness in predicting insurance risk categories using machine learning techniques. The XGBoost classifier achieved strong predictive performance when trained on the processed dataset, with evaluation metrics such as accuracy, precision, recall, and F1 score indicating reliable classification of policyholder risk levels. The use of the SMOTE technique successfully addressed the issue of class imbalance, resulting in improved prediction accuracy for minority risk classes. The ROC-AUC score further confirmed the model's ability to distinguish between different risk categories. The integration of SHAP explanations provided valuable insights into the factors influencing risk predictions, with variables such as smoking status, body mass index, and pre-existing diseases contributing significantly to higher risk scores. The continuous learning mechanism also proved beneficial, as periodic retraining allowed the model to adapt to newly collected data and maintain predictive relevance. Overall, the system demonstrated strong potential for supporting real-time insurance analytics and decision-making.

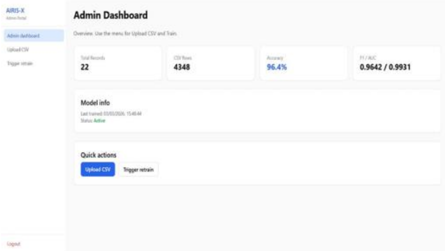
International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper











VII CONCLUSION

This study presented AIRIS-X, an intelligent real-time insurance risk prediction system that integrates machine learning, explainable artificial intelligence, and continuous learning capabilities. The system addresses several limitations of traditional insurance risk assessment methods, which often rely on static actuarial models that cannot effectively capture complex patterns in modern healthcare and lifestyle data. By leveraging the XGBoost machine learning algorithm, the proposed system is capable of identifying nonlinear relationships between user characteristics and insurance risk, enabling more accurate classification of policyholders into different risk categories. The integration of SMOTE improves model fairness by addressing class imbalance issues commonly present in insurance datasets. One of the key contributions of this research is the incorporation of SHAP-based explainable AI techniques, which provide transparent insights into the factors influencing model predictions. This transparency helps build trust among users and stakeholders while supporting regulatory compliance in automated decision systems. Additionally, the continuous learning framework allows the predictive model to evolve as new data is collected, ensuring that the system remains adaptive and relevant over time. The inclusion of policy recommendation features and a chatbot interface further enhances user engagement by providing personalized guidance and assistance.

The system's modular architecture, built using modern web technologies and scalable APIs, ensures efficient deployment and integration with existing insurance platforms. Overall, the AIRIS-X system demonstrates how intelligent analytics platforms can transform insurance risk assessment by combining predictive modelling, explainability, and adaptive learning to support more informed and transparent decision-making processes.

REFERENCES

1. Breiman, L. (2001). Random forests. Machine Learning.
2. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. KDD Conference.
3. Bishop, C. (2006). Pattern Recognition and Machine Learning. Springer.
4. Han, J., Kamber, M., & Pei, J. (2012). Data Mining: Concepts and Techniques. Morgan Kaufmann.
5. Friedman, J. (2001). Greedy function approximation: Gradient boosting machine. Annals of Statistics.
6. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.
7. Molnar, C. (2020). Interpretable Machine Learning. Lulu Press.
8. Ribeiro, M., Singh, S., & Guestrin, C. (2016). Why should I trust you? Explaining model predictions. KDD.
9. Lundberg, S., & Lee, S. (2017). A unified approach to interpreting model predictions. NIPS.
10. Chawla, N. et al. (2002). SMOTE: Synthetic minority oversampling technique. Journal of AI Research.
11. Witten, I., Frank, E., & Hall, M. (2016). Data Mining: Practical Machine Learning Tools.
12. Provost, F., & Fawcett, T. (2013). Data Science for Business.
13. Hastie, T., Tibshirani, R., & Friedman, J. (2009). Elements of Statistical Learning.
14. Jordan, M., & Mitchell, T. (2015). Machine learning trends. Science.
15. Kotu, V., & Deshpande, B. (2018). Predictive Analytics and Data Mining.
16. Russell, S., & Norvig, P. (2021). Artificial Intelligence: A Modern Approach.
17. Shalev-Shwartz, S., & Ben-David, S. (2014). Understanding Machine Learning.
18. Aggarwal, C. (2015). Data Mining: The Textbook.
19. Domingos, P. (2012). A few useful things to know about machine learning. Communications of the ACM.
20. Dietterich, T. (2000). Ensemble methods in machine learning. Multiple Classifier Systems.
21. Pedregosa, F. et al. (2011). Scikit-learn: Machine learning in Python. JMLR.
22. Paszke, A. et al. (2019). PyTorch: An imperative deep learning library. NeurIPS.
23. Chollet, F. (2018). Deep Learning with Python.

24. Géron, A. (2019). Hands-On Machine Learning with Scikit-Learn and TensorFlow.

25. Kuhn, M., & Johnson, K. (2013). Applied Predictive Modeling.

26. James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). Introduction to Statistical Learning.

27. Zhang, C., & Ma, Y. (2012). Ensemble Machine Learning.

28. Kelleher, J., Mac Namee, B., & D'Arcy, A. (2015). Fundamentals of Machine Learning.

29. Murphy, K. (2012). Machine Learning: A Probabilistic Perspective.

30. Bishop, C. (2007). Pattern recognition in predictive analytics.

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