Volume (1) No (8), 2025
Journal of Global Research in Multidisciplinary Studies (JGRMS)
Review Paper/Research Paper
Available online at https://saanvipublications.com/journals/index.php/jgrms/index

A Review of Machine Learning Techniques for Risk Evaluation in Healthcare and Insurance Systems

Dr. Prithviraj Singh Rathore
Assistant Professor
Department of Computer Sciences and Applications
Mandsaur University
Mandsaur
prathviraj.rathore@meu.edu.in

***Abstract*—As chronic diseases surge globally and insurance markets grow increasingly complex, traditional risk assessment frameworks are becoming obsolete. Static evaluations based on historical data and rigid actuarial models can no longer keep pace with the dynamic nature of individual health profiles or the rising volume of real-time behavioral and biomedical data. Machine learning (ML), with its capacity to analyze vast, high-dimensional, and heterogeneous datasets, is revolutionizing risk modeling in both healthcare and insurance sectors. This survey highlights the critical role of ML in accurately and proactively identifying, predicting, and managing risks. In healthcare, ML models enable disease prediction, patient risk stratification, early warning systems, and mortality forecasting by processing data from electronic health records, medical imaging, wearable devices, and genomics. In parallel, the insurance domain benefits from ML-driven claims prediction, fraud detection, customer segmentation, and dynamic underwriting using behavioral, demographic, and historical claims data. Techniques such as Random Forest, Support Vector Machines (SVM), Neural Networks, and Gradient Boosting (GB) are evaluated for their performance, interpretability, and flexibility. Key issues, including data fragmentation, model bias, and interpretability in high-stakes scenarios, are addressed. Grounded in state-of-the-art algorithms and real-world applications, this research demonstrates ML's transformative potential for individualizing, resilient, and data-driven healthcare and insurance systems.**

Keywords—Machine Learning (ML), Risk Assessment, Healthcare Analytics, Insurance Fraud Detection, Predictive Modeling, Patient Stratification, Claims Management.

I. INTRODUCTION

In today's, in world of speed and connectivity, everyone is more vulnerable to multiple health hazards, and chronic illnesses like diabetes, high blood pressure, and being overweight are on the rise around the world. Indeed, over 70% of deaths all over the world are related to chronic diseases which are may be as a result of sedentary lifestyles and unhealthy diet styles [1]. It was noted that 422 million people in the world have diabetes as stated in the WHO global report, and the condition is not yet slowing down. Likewise, the problem with hypertension is increasing in all populations, thus continuing to add to the world health burden.

This increasing rate of chronic illness also reveals the flaws in more generic health insurance models, which are usually based on fixed risk assessment. The existing programs in personalization focus on fixed information such as previous health records and questionnaires during the enrolment level which provide the health picture of the individual in a minute frame [2]. There is however growing acceptance that health is not fixed but rather dynamic and highly dependent on lifestyle choices, behaviour and bedside physiological measurements. As an example, diabetes prevention research studies have placed a strong focus on the importance of lifestyle in the health outcome, which in recent decades has seen a drastic increase in the levels of obesity and type II diabetes.

In response to this, Health Risk Assessments (HRAs) have come up as systematic set of assessments that help to measure risk at both the individual and population level depending on the lifestyle and medical history of the individual as well as biomarkers [3]. Although they may be beneficial, the challenge is still a problem in gathering such data, particularly on healthy populations. Poor engagement levels of wellness programs, including 24% of the Annual Wellness Visit of Medicare in 2017, indicate a main obstacle to successful risk assessment [4].

In parallel, financial institutions, such as insurers, are coming around to the realization that they ought to be on the offensive when addressing the risk. The financial stability requires precise prediction of losses and instantaneous adaption work where the conventional assessment techniques would be insufficient as a result of their incapability of managing the scale and complexity of contemporary data [5]. This is the area where machine learning (ML) has become a life changer [6]. ML algorithms can process immense and complicated datasets both structured and unstructured in nature-to identify hidden trends and predict risk trends, and automate decisions with an ever-growing level of accuracy.

These models constantly train on new data, and as they do, their accuracy increases, creating the possibility to shift towards proactive approaches to healthcare and insurance [7]. ML has now emerged as the primary tool in the contemporary risk assessment process, which utilizes information from medical records, lifestyle data, claims, and immediate biometrics to better predict health and financial outcomes. Decision trees (DT), support vector machines (SVM), neural networks (NN), and ensemble models are the common methods used to predict diseases, detect frauds, profile the risks posed by patients, and optimize underwriting processes. This overview considers the range of the possibilities of machine learning application to the field of health and insurance risks analysis and their advantages and drawbacks, and evaluates the way they can change the face of decision-making in these important spheres.

A. Structure of the Paper

This paper is structured as follows: Section II covers core concepts of risk assessment. Section III discusses machine learning applications in healthcare, including disease prediction and prognosis. Section IV focuses on ML use in insurance for claims prediction and fraud detection. Section V presents a literature review, and Section VI concludes with key findings and future research directions.

II. Concepts of Risk Assessment

There is a lengthy and distinguished history behind the concept of risk and risk assessments. Over 2400 years ago, the Athenians introduced the capacity to assess risk before making decisions (Bernstein 1996). However, the scientific field of risk assessment and management is very recent, having only been established for 30 to 40 years [8]. There are two primary tasks in the risk field: I) using risk assessments and risk management to study and treat the risk of specific activities (like an investment or an offshore installation operation); and II) conducting generic risk research and development related to concepts, theories, frameworks, approaches, principles, methods, and models to understand, assess, characterize, and communicate the risk of specific activities (like an investment or an offshore installation operation) [9]. The concepts and instruments for management and assessment that used in the I) circumstances are introduced in the general section II). In short, the risk area focuses on and should comprehend, evaluate, and manage the world (in terms of risk).

A. Risk Assessment in Insurance

Risk assessment in insurance refers to the systematic evaluation of factors that influence the likelihood and cost of future claims. Accurate risk evaluation is essential for determining policy premiums, structuring underwriting strategies, managing reserves, and ensuring the financial sustainability of insurers [10]. Historically, two types of actuarial models, which are based on historical claims data and pre-decided statistical assumptions, have been used by insurers. Though effective, such models do not always have the flexibility required to handle the large amount, variety, and velocity of current insurance data.

In the last few years, ML has made immense progress in streamlining risk analysis applications in insurance systems [2][11]. The ML algorithms enable the analysis of heterogeneous and high-dimensional data and the identification of underlying patterns, and give predictive insights that are not possible to be hidden by traditional methods. To review the literature, this review describes the currently existing practices in ML and the most frequently used ML practices in the context of insurance risk assessment, with the following key application areas:

1) Predictive Modeling for Claims Risk

ML models such as RF, SVM, and GBM are frequently used to predict the probability and future expenses of claims [12]. These models are based on characteristics such as age, comorbidities, historical claims, behavioral indicators, and environmental factors to make high accuracy predictions.

2) Fraud Detection

Insurance fraud is an on-going problem that causes great financial losses. authors have shown that ML-based anomaly detection such as Isolation Forests, Autoencoders, and Artificial Neural Networks (ANNs) can be efficacious in detecting fraudulent claims patterns. Unsupervised learning and semi-supervised techniques are also particularly useful where there is little labelled fraud training data.

3) Customer Segmentation and Risk Profiling

The unsupervised learning methods, including K-Means and DBSCAN clustering, are adopted to cluster the policyholders according to their behaviour, usage, and risk exposure. The segments allow tailor-made insurance products and services, micro marketing, and underwriting policy improvement.

4) Dynamic Underwriting

ML helps to provide adaptive underwriting models that recalculate and re-estimate the customer risk profile continuously in response to new information. This solution is a step in the right direction because it goes beyond single-time assessment of risks during the issuance of policies to more responsible and fair insurance systems.

B. Risk Factors in Healthcare

Healthcare risk factors emphasize the significance of preventative measures and equal access to healthcare by including behavioral, environmental, and socioeconomic characteristics that have a substantial impact on illness prevalence and outcomes.

- Health risk factors like tobacco use, nutrition, and alcohol use contribute to disease burden globally [13]. In low- and middle-income nations with inadequate access to healthcare, non-communicable illnesses are responsible for more than 70% of fatalities [14]. These factors exacerbate pre-existing inequalities and amplify challenges for vulnerable populations.
- Prevention is crucial in public health efforts, focusing on primary strategies like vaccination and healthy lifestyle education. Secondary measures aim for early disease detection and management [15]. However, societal variables, policy support, and financial limitations frequently result in inadequate implementation.

C. Risk Factors in Insurance

Risk factors for insurance include socioeconomic status, health behaviors, program characteristics, and demographics that affect healthcare utilisation and cost dynamics.

- Health insurance risks factors determine the likelihood of using healthcare services and the cost of care for patients with health insurance [16][17]. Age and chronic conditions increase claims and long-term utilization, affecting the economic viability of insurances.
- Insurance program duration affects risk, with longer members being more aware of benefits and using services more. However, lower usage can occur due to waiting times or customer dissatisfaction. Health-related behaviors like smoking, alcohol abuse, and inactivity increase health risks and medical expenses. Retention is crucial to prevent dropouts.

- Healthcare utilization is influenced by social-economic levels, education, and awareness of health insurance benefits [18], but can vary regionally and culturally. Program-related factors, such as premium prices and waiver policies, also play a role. Access to healthcare facilities, quality of care, and people's perception of system reliability also influence utilization patterns.

D. Common Challenges in Risk Assessment

The healthcare and insurance systems that rely on risk assessment also do not lack problems and challenges, even though advanced ML algorithms are used. Such difficulties may restrict the utility, reliability, and generalizability of the ML-based risk models.

1) Data Availability & Quality

Machine learning models need good and massive data to learn valuable patterns and make good projections. Nevertheless, currently, healthcare and insurance sectors are characterized by fragmented, incomplete or inconsistent data. Special information access may be limited further by the privacy laws and ownership of proprietary data.

2) Bias and Fairness

ML models can be biased due to historical inequalities or unbalance in data used for training. Incorrect representation of demographics or under-served demographics can disadvantage them in prediction, increasing existing disparities in care or insurance benefits access [19][20]. Fairness can be achieved through dataset design and algorithm modification.

3) Interpretability

Advanced ML techniques, such as ensemble approaches and DL, can be labelled as black boxes due to their complexity in interpreting human decision-making. Stakeholders, including clinicians, policymakers, and regulators, need interpretability to maintain confidence, reduce errors, and ensure transparency in risk assessments.

III. Machine Learning Applications in Healthcare Risk Assessment

Machine learning (ML) has transformed the healthcare sector through data-empowered insights that healthcare providers use to make better clinical decisions, prevent diseases, and better manage patients. Follow Figure 1 for ML models enable high-quality risk stratification, early identification, and planning of individual treatments by learning patterns drawn across various health data including electronic health records (EHRs), medical pictures, genomics, and wearable sensors. Some of the major areas of application in healthcare risk assessment include the following:

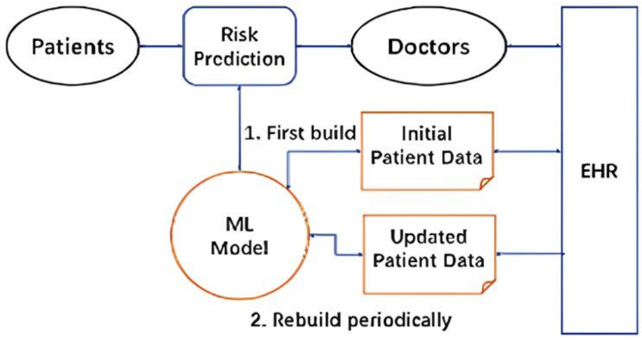

Fig. 1. Healthcare Risk Assessment

A. Disease Risk Prediction and Classification

Predictions about diseases and their classification often use Machine Learning (ML) techniques and a wide variety of diseases fall in this category, especially those that are chronic and high mortality, e.g. diabetes, cardiovascular diseases, cancer, respiratory disorders, and neurological illnesses. These models seek to either estimate the risk of a disease occurrence or to assign patients to various categories of diagnosis using past clinical information, which might be lab outcomes, vital statistics, genetic indications, imaging information, demographics, and lifestyle involved [21].

Supervised learning algorithms like SVMs, Random Forest, Decision Trees, and GBMs are used for binary or multiclass disease classification in healthcare datasets [22]. For instance, logistic regression and XG Boost models have successfully predicted Type 2 diabetes and pre-diabetes conditions.

Further, multi-modal learning that uses structured clinical information (with unstructured information like an image or text-based clinical data) is an area of interest that is seen to enhance the accuracy of predictions using complementary sources of information.

B. Patient Risk Stratification and Early Warning Systems

Risk stratification is an essential healthcare process that includes categorizing patients into three groups of low, medium, or high risks, considering their potential to have adverse clinical events. This method helps in prioritizing medical care and allocation of resources as well as individual treatment planning, particularly in high-reliability settings such as emergency departments and intensive care units (ICUs).

Machine learning models enable dynamic and continuous risk assessment by processing diverse patient data, including vital signs, laboratory findings, demographic factors, comorbidities and medication history, resulting in more accurate risk prediction [23].

The most modern Early Warning Systems (EWS) utilize time-series modelling approaches, including the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) neural nets, which can forecast clinical deterioration, including development of sepsis, cardiac arrest, respiratory failure, or necessity of ICU transfer. Such deep learning models come in especially handy in capturing time dependencies and pattern developments in vitals and lab trends of patients across time.

C. Prognosis and Mortality Risk Modeling

The prognostic modelling is critical in clinical decisions to estimate the development of the disease, survival time, or recurrence of the patient with acute, chronic, or terminal illnesses. Correct prognosis is vital in treatment planning, patient counselling, resource planning, and care pathways optimization particularly in the setting of oncology, cardiology, intensive care settings, and palliative care. Survival analysis and predictions of the time-to-event happenings have long been accomplished with the traditional means such as the Cox Proportional Hazards (CPH) model [24]. Although they work well on assumption that hazards are proportional, these models tend to be insensitive to non-linearities, high-dimensional data, and strong feature interactions that are common in modern healthcare data.

Machine learning enabled survival models have been created to solve these weaknesses. An interesting one is the Random Survival Forest (RSF) which is a non-parametric ensemble model which extends decision trees to censored data and nonlinear data. The predictive power in RSF has been well shown in predicting cancer recurrences, postoperative complications, and prediction of organ failure.

IV. Applications of Machine Learning in Insurance Risk Assessment

Insurance is one of the industries that are more likely to exploit machine learning (ML) to better determine the risks, streamline their operations, and make better decisions at each stage of the policy lifecycle [25]. ML-driven systems are becoming an addition or replacement to traditional actuarial models that would allow Real-time processing of massive volumes of both organized and unstructured data. The following four are the main spheres in which ML is changing the insurance risk management.

A. Predictive Modeling for Claims Management

Companies that take the claims management process seriously recognize the central role of predictive modelling in assisting the insurer to predict the number of claims that are on the way, how severe the claims might be, and in uncovering possible anomalies in the claims system. The models use various data sets- previous claims, policyholder demographics, behavioral pattern, environmental [26] factors (swings in weather, etc.), motor vehicle telemetry information (in auto), and health parameters (in health insurance) to draw an informed opinion of the risk ahead.

Algorithms Random Forest and Gradient Boosting Machines (GBMs) include some of the most effective ones in the said field characterized by high-accuracy and resilience when it comes to classification and regression. Such methods of ensemble learning can also be used to deal with large and complex data sets and can also reveal non-linear relationships which may be missed by conventional statistical approaches.

Insurers can also proactively manage resources, predict claim rushes, and enhance arrangements in efficiency by recognizing patterns and trends in the behaviour of claims and automatic triage and prioritization of the claims. Not only this saves time in the process, but it also increases customer satisfaction and saves overhead expenditures.

B. Customer Segmentation and Risk Profiling

Insurance sector data-driven decision-making is an in-complete without customer segmentation and risk profiling. Machine learning helps insurers to look at behavioral, demographic, and transactional data in order to segment policyholders into different risks. These divisions enable them to maximize resource use, devise customized policy plans and anticipate risks.

The segmentation tasks are usually performed by unsupervised learning algorithms that help distinguish different areas, for example, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), K-Means, and hierarchical clustering. They find natural clusters in the data of customers, not using pre-set labels, to allow the insurer insight into the similarities among customers, whether these are based on the speed at which they make claims or the risk behaviour or even the product preference [27].

Segmentation is knowledge that is used in informing various business functions such as:

- Specific marketing and promotions
- Individualized insurance cover and premiums
- High-risk, or fraudulent activity Early identification.

V. Literature Review

This section looks at the possible applications of ML in the fields of healthcare and risk assessment in the insurance sector, such as cases of frauds, readmission prediction, credit rating, and risk selections. They emphasize the competence of ML, such issues as data quality and ethics and infer future enhancement to enhance accuracy and transparency.

Brati, Braimllari and Gjeçi (2025) seeks to determine how well classification algorithms, such as Naïve Bayes, K-Nearest Neighbors, Random Forest, Decision Tree, Boost, and Logistic Regression, predict high insurance claims through empirical evaluation. The factors that affect how high-cost claims are classified, claims, cars, and insured parties are examined in this study. 802 observations of bodily injury claims from a private insurance company's vehicle liability portfolio in Albania, spanning the years 2018–2024, are used in this study [28].

Basyouni (2025) provided a theoretical basis and practical ML application in risk assessment and valuation processes. Using case studies in auditing (e.g., GL.ai, DARTbot) and operational risk (e.g., fraud detection and loss prediction), the article explains how ML helps better identify risk, increase accuracy, and enhance efficiency. It also discusses more specific items being addressed, such as data governance, model transparency and AI ethics, which it discusses through reference to COSO and regulatory guidance [29].

Panchangam et al (2024) developed a risk-based readmission prediction model with the discharge EMR data. The LACE plus score was then used to validate this model. Approximately 310,000 hospital admissions of individuals with cardiovascular and cerebrovascular disorders made up the research group. Lab findings, vitals, prescriptions, comorbidities, and admit/discharge settings were all included in the patients' EMR data [30].

Kleef et al. (2024) provided a framework for examining the extent of risk selection incentives and prospective insurer and consumer responses in these marketplaces. Three steps comprise strategy. Begin by outlining the four categories of risk selection: (a) consumer selection both within and outside of the market; (b) consumer selection between high- and low-value plans; (c) insurer selection through plan design; and (d) insurer selection through other channels like marketing, customer service, and supplemental insurance. The second phase is to provide a conceptual framework that explains how the health insurance markets' characteristics and regulations impact the incentives and extent of risk selection along these four dimensions. Third, apply this approach to examine nine regulated competition health insurance markets in the US, Europe, Israel, and Australia [31].

Suhadolnik, Ueyama and Silva (2023) used a dataset of more than 2.5 million observations from a financial institution to evaluate 10 machine learning methods. Recap the main statistical and machine learning models used in credit scoring and go over the most recent research results. According to findings, ensemble models perform better in credit classification than conventional methods like logistic regression, especially XG Boost. This study includes important stages of data processing, exploratory data analysis, modelling, and assessment metrics, making it a useful resource for researchers and credit risk specialists [32].

Amponsah, Adekoya and Weyori (2022) developed a health model that can automatically identify financial fraud in Saudi Arabian health insurance claims. The model accurately predicts the biggest contributing factor to fraud. Using three supervised deep and machine learning techniques, the labelled imbalanced dataset was examined. Three healthcare providers in Saudi Arabia provided the dataset. The models that were used were artificial neural networks, logistic regression, and random forest [33].

Table I highlights ML's effectiveness in healthcare and insurance risk assessment, addressing prediction accuracy, fraud detection, and policy insights, while noting challenges like data quality, transparency, and suggesting broader, real-time, explainable applications.

TABLE I. SUMMARY OF RECENT STUDIES ON RISK ASSESSMENT FOR HEALTHCARE AND INSURANCE SYSTEMS

Reference	Study On	Approach	Key Findings	Challenges	Future Direction
Brati, Braimllari and Gjeçi (2025)	Predicting high insurance claims (motor liability)	ML algorithms: LR, DT, RF, Boost, KNN, SVM, NB; dataset of 802 claims	ML algorithms can effectively classify high-cost claims; identifies variables influencing claims	Small dataset; domain-specific (motor insurance)	Use larger, diverse datasets; explore deep learning approaches
Basyouni (2025)	ML in risk assessment and valuation (auditing & operational risk)	Case studies: GL.ai, DARTbot, fraud detection, loss prediction; discusses governance & ethics	ML improves risk identification, accuracy, efficiency; addresses transparency & ethics issues	Data governance, model transparency, ethical concerns	Develop more transparent and regulated ML frameworks
Panchangam et al. (2024)	Hospital readmission risk prediction	ML model trained on EMR data of 310,000 admissions; validated with LACE+ score	EMR-based ML model predicts readmission risk effectively for cardiovascular/cerebrovascular patients	Integration with clinical workflows; data quality issues	Apply to other diseases; real-time deployment in hospitals
Kleef et al. (2024)	Risk selection in health insurance markets	Conceptual framework analyzing consumer & insurer behavior and regulation across 9 markets	Identifies 4 types of risk selection and regulatory influences in various markets	No ML used; focus is conceptual & policy-oriented	Integrate ML-based insights into policy frameworks
Suhadolnik, Ueyama and Da Silva (2023)	Financial firms' credit risk scoring	Evaluated 10 ML algorithms on 2.5M observations; compares traditional & ensemble methods	Ensemble models (XGBoost) outperform traditional methods like logistic regression	Model interpretability; managing large datasets	Incorporate explainable AI and test on real-time data
Amponsah, Adekoya and Weyori (2022)	Fraud detection in health insurance claims (Saudi Arabia)	ML models: RF, LR, ANN; dataset from 3 providers	Identified key contributors to fraud; achieved high accuracy in detection	Dataset imbalance and applicability to different areas	Test in broader contexts; improve model handling of imbalance

VI. CONCLUSION AND FUTURE WORK

ML has been a revolutionary tool for improving the precision and effectiveness of, and personalization of risk assessment across healthcare and insurance domains. By leveraging complex and high-dimensional datasets, ML algorithms offer superior predictive capabilities compared to traditional actuarial and statistical models. In healthcare, they enable early disease detection, patient risk stratification, and prognosis modelling using inputs from electronic health records, genomic data, and wearable sensors. In insurance, ML supports fraud detection, customer segmentation, claims prediction, and dynamic underwriting through analysis of behavioral, demographic, and environmental factors. Despite significant advancements, several challenges remain. Issues such as data fragmentation, model interpretability, fairness, and potential bias hinder large-scale deployment and trust in ML-driven systems. The "black-box" nature of many DL models limits stakeholder transparency, while disparities in training data can perpetuate unequal outcomes in both healthcare access and insurance benefits.

Future research should concentrate on integrating fairness-aware algorithms to solve ethical issues and improving model interpretability using explainable AI (XAI) frameworks. Additionally, integration of federated learning can support privacy-preserving model training on distributed health and insurance data. To evaluate models in real-world scenarios and guarantee regulatory compliance, data scientists, physicians, insurers, and legislators must collaborate across disciplines.

REFERENCES

[1] S. E. Abhadiomhen, E. O. Nzeakor, and K. Oyibo, "Health Risk Assessment Using Machine Learning: Systematic Review," *Electronics*, vol. 13, no. 22, Nov. 2024, doi: 10.3390/electronics13224405.

[2] A. Pnevmatikakis, S. Kanavos, G. Matikas, K. Kostopoulou, A. Cesario, and S. Kyriazakos, "Risk Assessment for Personalized Health Insurance Based on Real-World Data," *Risks*, vol. 9, no. 3, 2021, doi: 10.3390/risks9030046.

[3] H. Park *et al.*, "Lowering Barriers to Health Risk Assessments in Promoting Personalized Health Management," *J. Pers. Med.*, vol. 14, no. 3, Mar. 2024, doi: 10.3390/jpm14030316.

[4] A. Misra and J. T. Lloyd, "Hospital utilization and expenditures among a nationally representative sample of Medicare fee-for-service beneficiaries 2 years after receipt of an Annual Wellness Visit," *Prev. Med. (Baltim).*, vol. 129, Dec. 2019, doi: 10.1016/j.ypmed.2019.105850.

[5] S. A. Farooqi, "The Role Of Machine Learning In Risk Assessment And Management In Finance," *J. Policy Res.*, vol. 3, no. 2, pp. 680–686, 2025, doi: 10.5281/zenodo.14963077.

[6] N. Prajapati, "The Role of Machine Learning in Big Data Analytics: Tools, Techniques, and Applications," *ESP J. Eng. Technol. Adv.*, vol. 5, no. 2, pp. 16–22, 2025, doi: 10.56472/25832646/JETA-V5I2P103.

[7] S. J. Wawge, "A Survey on the Identification of Credit Card Fraud Using Machine Learning with Precision, Performance, and Challenges," *Int. J. Innov. Sci. Res. Technol.*, vol. 10, no. 4, 2025, doi: 10.38124/ijisrt/25apr1813.

[8] M. Eling, I. Gemmo, D. Guxha, and H. Schmeiser, "Big data, risk classification, and privacy in insurance markets," *Geneva Risk Insur. Rev.*, vol. 49, no. 2, pp. 75–126, Mar. 2024, doi: 10.1057/s10713-024-00098-5.

[9] P. Dhanekulla, “Real-Time Risk Assessment in Insurance: A Deep Learning Approach to Predictive Modeling,” *Int. J. Multidiscip. Res.*, vol. 6, no. 6, pp. 1–11, 2024, doi: 10.36948/ijfmr.2024.v06i06.31710.

[10] A. Owen and E. Oye, “AI-Driven Contextual Health Risk Assessment: A Comprehensive Approach to Personalized Healthcare,” 2025.

[11] H. Kali, “Optimizing Credit Card Fraud Transactions Identification and Classification in Banking Industry Using Machine Learning Algorithms,” *Int. J. Recent Technol. Sci. Manag.*, vol. 9, no. 11, pp. 85–96, 2024.

[12] V. Varadarajan and V. K. Kakumanu, “Evaluation of risk level assessment strategies in life Insurance: A review of the literature,” *J. Auton. Intell.*, vol. 7, no. 5, 2024, doi: 10.32629/jai.v7i5.1147.

[13] M. Brauer *et al.*, “Global burden and strength of evidence for 88 risk factors in 204 countries and 811 subnational locations, 1990--2021: a systematic analysis for the Global Burden of Disease Study 2021,” *Lancet*, vol. 403, no. 10440, pp. 2162–2203, 2024.

[14] P. Ferrara, “Health Risk Factors, Prevention, and Inequalities,” *Medicina (B. Aires).*, vol. 61, no. 1, Jan. 2025, doi: 10.3390/medicina61010127.

[15] M. A. Kelly *et al.*, “Distilling the Fundamentals of Evidence-Based Public Health Policy,” *Public Heal. Reports®*, vol. 140, no. 1, pp. 40–47, Jan. 2025, doi: 10.1177/00333549241256751.

[16] S. Ghimire, S. Ghimire, P. Khanal, R. A. Sagtani, and S. Paudel, “Factors affecting health insurance utilization among insured population: evidence from health insurance program of Bhaktapur district of Nepal,” *BMC Health Serv. Res.*, vol. 23, no. 1, Feb. 2023, doi: 10.1186/s12913-023-09145-9.

[17] M. A. Mostafiz, “Machine Learning for Early Cancer Detection and Classification: AIBased Medical Imaging Analysis in Healthcare,” *Int. J. Curr. Eng. Technol.*, vol. 15, no. 03, pp. 1–10, 2025.

[18] N. Malali, “Predictive AI for Identifying Lapse Risk in Life Insurance Policies: Using Machine Learning to Foresee and Mitigate Policyholder Attrition,” *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 5, no. 5, pp. 1–11, 2025.

[19] E. Veitch and O. A. Alsos, “A systematic review of human-AI interaction in autonomous ship systems,” *Saf. Sci.*, vol. 152, 2022, doi: 10.1016/j.ssci.2022.105778.

[20] S. R. P. Madugula and N. Malali, “AI-Powered Life Insurance Claims Adjudication Using LLMs and RAG Architectures,” *Int. J. Sci. Res. Arch.*, vol. 15, no. 1, pp. 460–470, Apr. 2025, doi: 10.30574/ijsra.2025.15.1.0867.

[21] C. B. C. Latha and S. C. Jeeva, “Improving the accuracy of prediction of heart disease risk based on ensemble classification techniques,” *Informatics Med. Unlocked*, vol. 16, 2019, doi: 10.1016/j.imu.2019.100203.

[22] S. Pandya, “Predictive Modeling for Cancer Detection Based on Machine Learning Algorithms and AI in the Healthcare Sector,” *TIJER – Int. Res. J.*, vol. 11, no. 12, 2024.

[23] B. Dimitrov, L. Forni, D. Hargreaves, L. Hodgson, C. Stubbs, and R. Venn, “Predicting escalation to intensive care in patients with suspected infection: Derivation of a clinical prediction rule: UPA3,” *J. Intensive Care Soc.*, 2016.

[24] S. Shin *et al.*, “Machine learning vs. conventional statistical models for predicting heart failure readmission and mortality,” *ESC Hear. Fail.*, vol. 8, no. 1, pp. 106–115, Feb. 2021, doi: 10.1002/ehf2.13073.

[25] S. Pandya, “A Machine and Deep Learning Framework for Robust Health Insurance Fraud Detection and Prevention,” *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 3, no. 3, pp. 1332–1342, Jul. 2023, doi: 10.48175/IJARSCT-14000U.

[26] C. Clemente, G. R. Guerreiro, and J. M. Bravo, “Modelling Motor Insurance Claim Frequency and Severity Using Gradient Boosting,” *Risks*, vol. 11, no. 9, Sep. 2023, doi: 10.3390/risks11090163.

[27] P. Riefler, A. Diamantopoulos, and J. A. Siguaw, “Cosmopolitan consumers as a target group for segmentation,” *J. Int. Bus. Stud.*, vol. 43, no. 3, pp. 285–305, Apr. 2012, doi: 10.1057/jibs.2011.51.

[28] E. Brati, A. Braimllari, and A. Gjeçi, “Machine Learning Applications for Predicting High-Cost Claims Using Insurance Data,” *Data*, vol. 10, no. 6, Jun. 2025, doi: 10.3390/data10060090.

[29] A. Basyouni, “Machine Learning for Risk Assessment in Audit and Operational Risk Management Machine Learning for Risk Assessment in Audit and Operational Risk Management.” 2025. doi: 10.13140/RG.2.2.30880.08964.

[30] P. V. R. Panchangam, T. A, T. B U, and M. J. Maniaci, “Machine Learning-Based Prediction of Readmission Risk in Cardiovascular and Cerebrovascular Conditions Using Patient EMR Data,” *Healthcare*, vol. 12, no. 15, Jul. 2024, doi: 10.3390/healthcare12151497.

[31] R. C. Van Kleef *et al.*, “Scope and Incentives for Risk Selection in Health Insurance Markets With Regulated Competition: A Conceptual Framework and International Comparison,” *Med. Care Res. Rev.*, vol. 81, no. 3, pp. 175–194, Jun. 2024, doi: 10.1177/10775587231222584.

[32] N. Suhadolnik, J. Ueyama, and S. Da Silva, “Machine Learning for Enhanced Credit Risk Assessment: An Empirical Approach,” *J. Risk Financ. Manag.*, vol. 16, no. 12, p. 496, Nov. 2023, doi: 10.3390/jrfm16120496.

[33] A. A. Amponsah, A. F. Adekoya, and B. A. Weyori, “A novel fraud detection and prevention method for healthcare claim processing using machine learning and blockchain technology,” *Decis. Anal. J.*, 2022, doi: 10.1016/j.dajour.2022.100122.