iJRASET

International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IX Month of publication: September 2026

DOI: https://doi.org/10.22214/ijraset.2026.84977

Smart Health Insurance Claim Guidance and Rejection Prediction System: An Explainable Approach to Preliminary Claim Assessment and Fraud-Risk Analysis

Katakam Nithin[1], Banam Varshini Priyamvada[2]
[1]PG Scholar, Dept. of Computer Applications, School of Informatics, Aurora Higher Education and Research Academy Deemed-to-be-University, Uppal, Hyderabad, Telangana, India
[2]Assistant Professor, Dept. of Computer Applications, School of Informatics, Aurora Higher Education and Research Academy Deemed-to-be-University, Uppal, Hyderabad, Telangana, India

Abstract: Health insurance claim processing is difficult for both policyholders and administrative teams because a claim outcome depends on many interacting factors, such as policy validity, coverage limits, waiting periods, pre-existing conditions, clinical-code compatibility, documentation completeness, hospital-network status, billing accuracy and prior claim history. Policyholders frequently do not understand why a claim is rejected, while hospitals and insurers need a structured way to screen claims before detailed manual review. This paper presents a Smart Health Insurance Claim Guidance and Rejection Prediction System, a web-based application built with React, TypeScript, Vite, Node.js, Express and Tailwind CSS that offers preliminary, explainable claim guidance. A rule-based claim-evaluation engine examines policy, financial, clinical, documentation and fraud-related factors to generate an approval/rejection probability, a confidence score, feature-level explanations similar to SHAP attributions, probable rejection reasons, and fraud-risk flags. The system provides role-based workflows for patients, hospitals and administrators, along with policy-document analysis, claim history, bulk claim processing and model-analytics dashboards. Functional and scenario-based validation across twelve claim scenarios confirmed that the implemented decision logic behaves as designed. Since the prototype does not yet include a trained machine-learning model or a labelled real-world dataset, its performance indicators are treated as prototype dashboard values rather than validated experimental results. The system nevertheless demonstrates a practical, explainable and extensible approach to preliminary health-insurance claim guidance.
Keywords: Health Insurance, Claim Rejection Prediction, Explainable AI, Fraud Detection, Rule-Based Engine, Policy Analysis, React, Node.

I. INTRODUCTION

Health insurance helps individuals manage the financial burden of medical treatment, but the process of getting a claim approved is rarely simple. A single claim may depend on policy validity, remaining sum insured, waiting periods, pre-existing-condition clauses, diagnosis and treatment codes, hospital-network status, required documents and billing accuracy, all of which must be evaluated together.

For policyholders, the biggest difficulty is understanding why a claim is rejected or only partially approved. Reasons may include exclusions, insufficient coverage, missing documents, waiting-period restrictions, incorrect medical codes or billing discrepancies, and when this information is not presented clearly, users struggle to take corrective action. Hospitals and insurance administrators likewise need a structured, repeatable way to screen claims before committing them to detailed manual adjudication.

To address this problem, we developed the Smart Health Insurance Claim Guidance and Rejection Prediction System — a centralized web platform that evaluates important policy, clinical, financial and documentation parameters and returns an indicative approval or rejection outcome, together with the reasons and risk indicators behind it. Rather than returning only a final status, the system exposes the factors that drove the result, helping users identify issues early and helping administrative teams prioritise claims that need human review.

The main features of the proposed system are:
- Role-based workflows for patients, hospitals and administrators
- A rule-based claim-evaluation engine covering policy, financial, clinical, documentation and network factors
- Preliminary approval/rejection probabilities with a confidence score
- SHAP-style, feature-level explanations for each prediction
- Fraud and anomaly indicators (clinical-code mismatch, billing outliers, claim-frequency flags)
- Policy-document analysis with a deterministic fallback engine
- Claim history, bulk claim upload and model-analytics dashboards

II. LITERATURE SURVEY

A. Johnson and Khoshgoftaar (2019)
Johnson and Khoshgoftaar proposed "Medicare Fraud Detection Using Neural Networks." The study applied deep neural networks to Medicare Part B claims to identify fraudulent activities and addressed severe class imbalance in the data. The results demonstrated the potential of neural networks for large-scale healthcare fraud detection. However, the study focused on fraud detection and did not address claim rejection prediction or policy-based claim guidance. [1]

B. Kaushik et al. (2022)
Kaushik et al. proposed "Machine Learning-Based Regression Framework to Predict Health Insurance Premiums." The study used an artificial-neural-network regression approach to estimate health insurance premiums from relevant insurance and demographic factors. The results showed that machine learning can support automated insurance cost estimation. However, the work focused on premium prediction rather than claim approval, rejection reasons, or policy coverage analysis. [2]

C. Health Insurance Cost Prediction Using Machine Learning (2022)
The study "Health Insurance Cost Prediction Using Machine Learning" investigated machine learning techniques for estimating medical insurance costs using the Medical Cost Personal dataset. Linear Regression and related predictive approaches were applied to identify relationships between input characteristics and insurance costs. The work demonstrated the usefulness of machine learning for healthcare cost estimation. However, it addressed cost prediction alone and did not provide claim rejection guidance or policy-document analysis. [3]

D. Nabrawi and Alanazi (2023)
Nabrawi and Alanazi proposed "Fraud Detection in Healthcare Insurance Claims Using Machine Learning." Random Forest, Logistic Regression, and Artificial Neural Networks were compared for identifying fraudulent healthcare insurance claims, with Random Forest performing strongly after class balancing using SMOTE. The study demonstrated the effectiveness of machine learning for fraud detection. However, it concentrated on fraudulent-claim identification and did not integrate policy interpretation, claim rejection prediction, or user-oriented guidance. [4]

E. Debener, Heinke and Kriebel (2023)
Debener, Heinke, and Kriebel proposed "Detecting Insurance Fraud Using Supervised and Unsupervised Machine Learning." The study compared supervised XGBoost with unsupervised Isolation Forest approaches for detecting suspicious insurance activity within an insurer investigation workflow. The comparison demonstrated the usefulness of both labelled and anomaly-detection approaches. However, the work primarily addresses fraud investigation and does not provide an integrated claim-assessment and policy-guidance platform. [5]

F. Settipalli and Gangadharan (2023)
Settipalli and Gangadharan proposed "WMTDBC: An Unsupervised Multivariate Analysis Model for Fraud Detection in Health Insurance Claims." The study introduced an unsupervised multivariate approach for identifying anomalous healthcare insurance claims without depending on labelled fraud data. The approach is useful where reliable labelled datasets are difficult to obtain. However, the method focuses on anomaly detection and does not cover claim rejection explanations, policy conditions, or comprehensive claim guidance. [6]

G. Hancock et al. (2023)

Hancock et al. presented "Explainable Machine Learning Models for Medicare Fraud Detection." The study investigated explainable machine learning models for detecting fraud in large-scale Medicare claims and emphasized transparency in model decisions. The research demonstrates the importance of interpretable outputs when AI is used in healthcare fraud detection. However, its primary focus remains fraud detection and does not extend to policy analysis or preliminary claim rejection prediction. [7]

H. Shekhar, Leder-Luis and Akoglu (2023)

Shekhar, Leder-Luis, and Akoglu proposed "Unsupervised Machine Learning for Explainable Health Care Fraud Detection." The study explored unsupervised learning methods for detecting healthcare fraud while improving the interpretability of detected patterns. The approach is useful for identifying suspicious behaviour when labelled examples are limited. However, the study does not combine fraud detection with policy validation, documentation checks, and claim-specific rejection guidance. [8]

I. Aarati, Shirisha and Bindhu (2023)

Aarati, Shirisha, and Bindhu investigated "Identifying Health Insurance Claim Frauds Using Machine Learning Concept." The study compared machine learning classifiers including Support Vector Machine, Decision Tree, K-Nearest Neighbour, and Logistic Regression for healthcare claim-fraud classification. The research demonstrated that classification algorithms can support automated fraud identification. However, the work is limited to fraud classification and does not provide integrated policy analysis or explainable claim rejection prediction. [9]

J. Permai and Herdianto (2023)

Permai and Herdianto proposed "Prediction of Health Insurance Claims Using Logistic Regression and XGBoost Methods." The study combined Logistic Regression and XGBoost for predicting suspicious health insurance claims. The approach demonstrates the potential of supervised learning for identifying claims that may require additional review. However, the prediction task does not by itself explain policy-related rejection causes or provide a complete claim-guidance workflow. [10]

K. Villegas-Ortega et al. (2025)

Villegas-Ortega et al. proposed a methodology for detecting suspicious health insurance claims using supervised machine learning. The methodology followed multiple phases for processing and analysing a large health insurance claims dataset and was evaluated on millions of claims from Peru. The study demonstrates the scalability of machine-learning-based suspicious-claim detection. However, the approach is primarily designed for fraud or suspicious-claim detection and does not integrate policy interpretation and user-facing rejection guidance. [11]

L. Kolambe and Kaur (2024)

Kolambe and Kaur proposed "Insurance Policy Summarization Using Natural Language Processing (NLP)." The study applied NLP techniques to summarise lengthy insurance policies and present important information in a more accessible form for policyholders. The work demonstrates the value of NLP for simplifying complex insurance documents. However, policy summarization alone does not predict claim outcomes or identify the specific reasons a claim may be rejected. [12]

M. Sbodio et al. (2024)

Sbodio et al. presented a collaborative artificial intelligence system for healthcare-claim compliance investigation. The approach extracts structured, machine-executable rules from policy documents to support compliance analysis. The study demonstrates how policy text can be transformed into actionable rules for automated investigation. However, it is oriented toward compliance investigators and does not combine policy rules with claim prediction, fraud indicators, and multi-role claim guidance. [13]

N. Muhammad et al. (2025)

Muhammad et al. investigated fraud detection and explanation in medical claims using Graph Neural Network architectures. The approach models relationships within medical-claim networks to identify suspicious patterns and provide explanations for detected fraud. The study demonstrates the usefulness of graph-based learning for complex claim relationships. However, the approach focuses on fraud detection and does not provide an integrated framework for policy validation, claim rejection prediction, and user guidance. [14]

O. Li et al. (2025)

Li et al. proposed "Textual Analysis of Insurance Claims with Large Language Models." The study investigated large language models for analysing insurance claim narratives and identifying textual discrepancies. The approach demonstrates the potential of modern language models for extracting and comparing information from unstructured claim text. However, textual discrepancy detection alone does not provide complete policy analysis, claim-outcome prediction, or actionable rejection guidance. [15]

Research Gap

The reviewed studies demonstrate significant progress in healthcare insurance fraud detection, cost prediction, suspicious-claim identification, policy summarization, compliance analysis, and textual claim processing. However, these capabilities are largely addressed as separate point solutions. Limited work combines policy-condition validation, financial and clinical checks, documentation review, fraud indicators, explainable claim prediction, and user-oriented guidance within a single multi-role platform. The proposed Smart Health Insurance Claim Guidance and Rejection Prediction System addresses this integration gap by bringing these functions together to provide preliminary, explainable claim assessment for patients, hospitals, and administrators.

III. SYSTEM ARCHITECTURE

The system follows a client–server architecture divided into three functional areas:

1) Patient Module – claim submission, claim history, prediction results, policy viewing and profile management.
2) Hospital Module – claim processing and bulk claim upload for hospital-side workflows.
3) Administrator Module – claims review, fraud detection, reporting, model analytics, patient management and system settings.

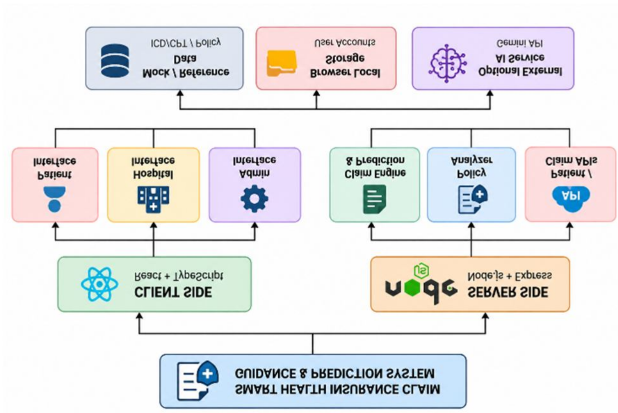


Figure 3.1 – High-Level System Architecture (Client–Server, Role-Based)

The React and TypeScript client communicates with an Express/Node.js server through REST-style endpoints such as /api/claims, /api/predict, /api/policy/analyze, /api/ai-audit and /api/patients. The current prototype uses TypeScript interfaces and in-memory/mock data together with browser localStorage for account persistence, rather than a conventional SQL/NoSQL database; the architecture is designed so this layer can later be replaced with MySQL or PostgreSQL without changing the overall workflow. An optional external AI service can be used for natural-language policy analysis, with a deterministic rule-based engine as fallback.

IV. METHODOLOGY

The claim-guidance process follows a structured pipeline:

1) Collect claim, policy and patient details
2) Validate policy status, coverage and waiting periods
3) Check clinical-code (ICD-10/CPT) compatibility
4) Check documentation completeness
5) Check hospital-network status and billing accuracy
6) Compute a rule-based rejection score
7) Generate feature-level (SHAP-style) explanations
8) Evaluate fraud/anomaly indicators
9) Generate a recommendation for the user or administrator

A. *Claim Evaluation Engine*

The core evaluation logic, implemented in runMLPrediction(), accumulates a deterministic rejection score from policy status, remaining sum insured, waiting period, pre-existing-condition conflicts, ICD-10/CPT concordance, documentation completeness, hospital-network status, billing anomalies, itemised-bill mismatch and prior-claim frequency. The accumulated score is converted into a rejection probability, bounded between 0.02 and 0.98, and the corresponding approval probability determines the outcome: 'Likely Approved' at 72% or above, 'Likely Rejected' at 38% or below, and 'Needs Review' in between.

B. *Explainability Module*

Each prediction is accompanied by SHAP-style feature attributions — for example, a financial-category factor such as 'Sum Insured Limit' with its value, its impact on the outcome and a short description — so that positive impact values indicate pressure toward rejection and negative values indicate pressure toward approval. This lets patients and administrators see why a result was produced rather than only what the result is.

C. *Fraud and Policy Analysis*

Fraud-oriented rules generate structured flags of low, medium or high severity from indicators such as clinical-code mismatch, billing outliers and unusual claim frequency, combined into an overall fraud score. A separate policy-analysis module (POST /api/policy/analyze) evaluates policy validity, waiting periods, illness-specific restrictions, pre-existing conditions, room-rent limits, sub-limits, co-payment and remaining sum insured, returning approved amount, deductions and clause references, either through an external AI service or the deterministic fallback engine.

V. SYSTEM WORKFLOW

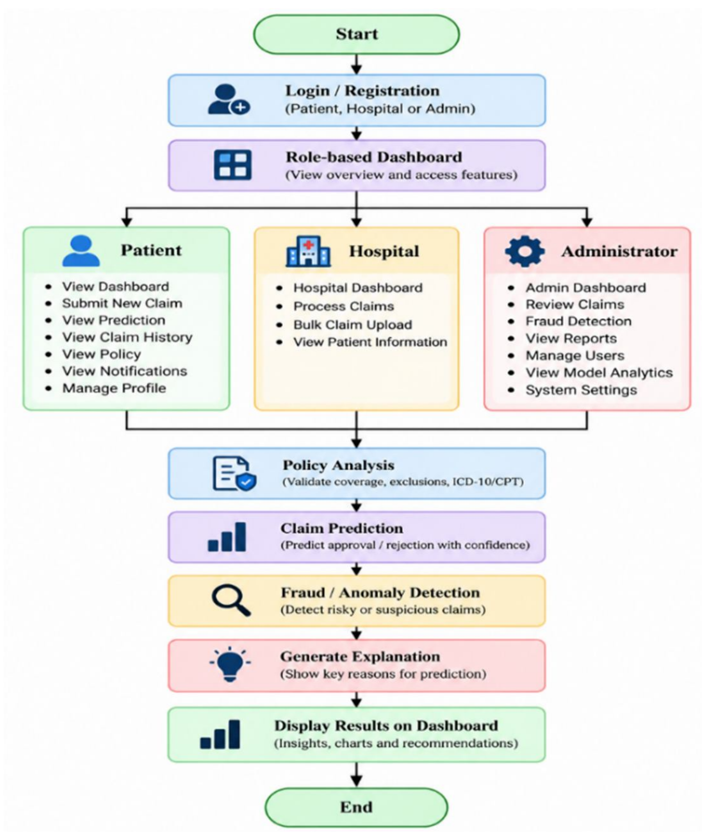


Figure 5.1 – Claim Submission and Prediction Workflow

User → Claim Submission → API → Claim Evaluation Engine → Policy / Clinical / Financial Checks → Prediction & Risk Analysis → Explanation → Role-Based Dashboard.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IX Sep 2026- Available at www.ijraset.com

A. Claim Prediction Process

1) Patient submits claim details through the UI
2) Request reaches the Express API (/api/predict)
3) Policy, financial, clinical and documentation checks run
4) A rejection score and probability are computed
5) Feature-level explanations and fraud flags are generated
6) The prediction, reasons and recommendation are returned
7) Results are shown on the patient/administrator dashboard

VI. IMPLEMENTATION

A. Frontend

Built with React, TypeScript and Vite, styled with Tailwind CSS. Role-specific interfaces include the Patient Dashboard, New Claim Submission, Claim Prediction Result, My Claims/Claim Detail, My Policy, the Hospital Dashboard with Bulk Claim Upload, and the Administrator suite (Claims Review Queue, Fraud Detection Hub, Reports, Model Analytics, User Management, System Settings).

B. Backend

Node.js and Express, written in TypeScript, expose REST endpoints for authentication, claim submission, bulk processing, prediction, policy analysis, AI audit, reference clinical codes, and patient/model analytics. The server also contains an ICD-10/CPT reference map used to check code–diagnosis compatibility and typical cost ranges.

C. Data and Security

The current prototype uses TypeScript interfaces, mock/reference datasets and browser localStorage rather than a persistent database, and supports three authenticated roles — patient, hospital and administrator — with role-based dashboard routing. Production deployment would require a secure persistent database, stronger authentication, encrypted storage and audit logging.

VII. EXPERIMENTAL RESULTS

A. Patient Dashboard

The patient dashboard provides a consolidated view of the policy and claim status. It displays information such as the remaining sum insured, total claims billed, claims under adjudication, settled claims, policy details, and recent claim activity.

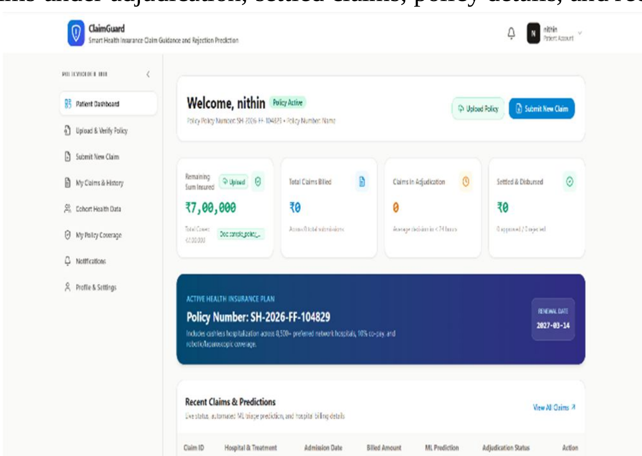


Figure 7.1 Patient dashboard showing policy coverage, claim activity, and claim status overview.

B. Claim Prediction

The claim prediction section provides the main output of the claim-evaluation engine. After claim information is submitted, the system evaluates policy status, coverage limits, waiting periods, pre-existing conditions, ICD-10/CPT compatibility, documentation, hospital network status, billing conditions, and previous claim frequency.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IX Sep 2026- Available at www.ijraset.com

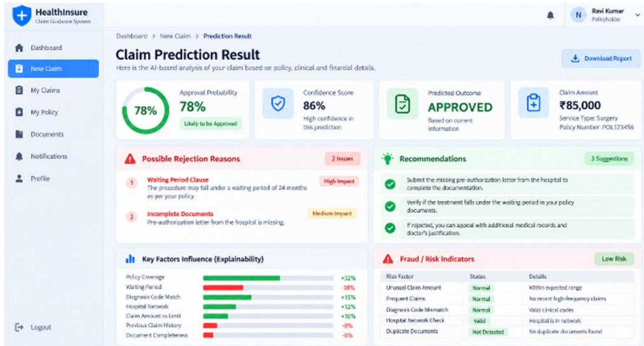


Figure 7.2 Claim prediction result showing approval probability, confidence score, rejection reason, and recommendation.

C. Explainable Claim Assessment

The explainability section presents the major factors contributing to the prediction. Each factor contains the feature name, value, impact, description, and category.

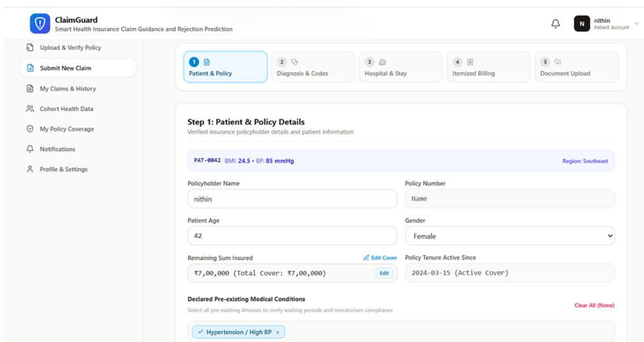


Figure 7.3. Explainable claim prediction showing feature-level contribution to the result.

D. Fraud and Anomaly Detection

The fraud-detection section provides an overview of potentially suspicious claims and their associated risk indicators. The system checks for clinical-code mismatches, billing outliers, itemised-bill reconciliation differences, and unusual previous-claim frequency.

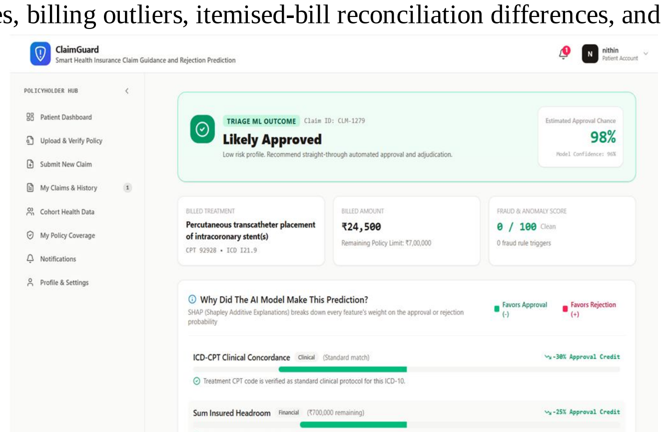


Figure 7.4 Fraud and anomaly detection dashboard showing identified risk indicators.

E. Policy Document Analysis

The policy analysis section allows policy information to be evaluated against the submitted claim context. The system analyses coverage conditions, waiting periods, exclusions, co-payment, room-rent limits, disease-specific restrictions, non-medical expenses, and remaining sum insured.

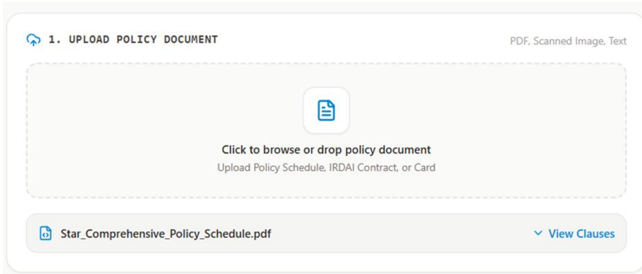


Figure 7.5 Policy document analysis showing coverage status, deductions, and clause references.

F. Hospital Claim Processing

The hospital interface provides a separate workflow for processing inpatient and daycare claims. It includes the hospital dashboard, pre-authorisation queue, claim status information, and bulk claim-upload functionality.

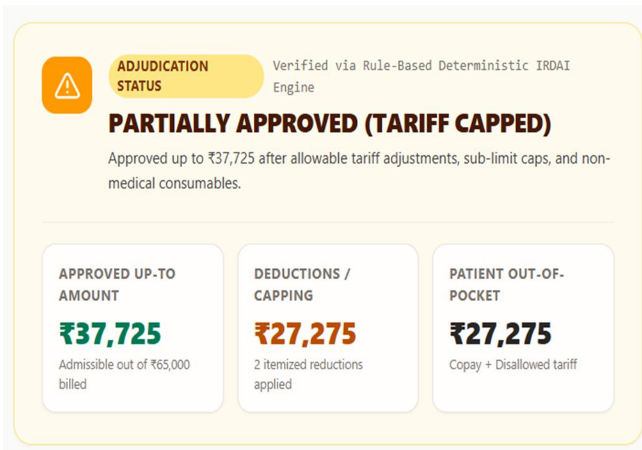


Figure 7.6. Hospital dashboard showing claim processing and pre-authorisation information.

G. Administrative Claims Review

The administrator module provides a claim-review queue where submitted claims can be filtered and prioritised according to prediction outcome, fraud score, and processing status.

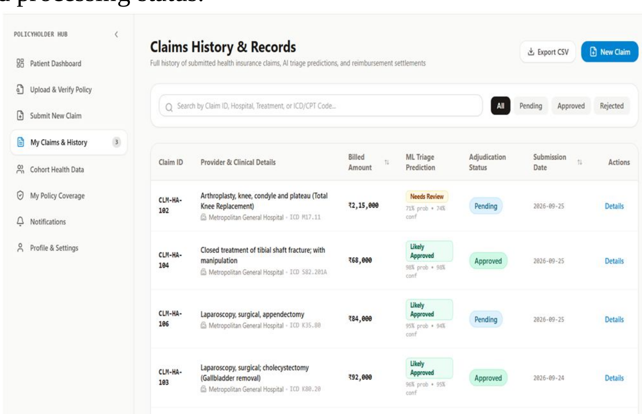


Figure 7.7. Administrator claims adjudication queue showing prediction and fraud-risk information.

H. Testing Summary

Functional validation was performed across twelve representative claim scenarios covering policy status, coverage, waiting periods, pre-existing conditions, ICD-10/CPT compatibility, documentation, hospital-network status, billing reconciliation, claim frequency, and fallback behaviour.

Validation Area	Scenarios Checked	Confirmed	Failures Found
Policy status / coverage	2	2	0
Waiting period / pre-existing	2	2	0
ICD-10 / CPT compatibility	2	2	0
Documentation completeness	1	1	0
Hospital network status	1	1	0
Billing / itemised reconciliation	2	2	0
Claim frequency / fraud flags	1	1	0
Fallback conditions	1	1	0
Total	12	12	0

Table 7.1. Functional Validation Summary

VIII. COMPARISON WITH OTHER METHODS

Feature	Basic Claim Tracker	Standalone Fraud-ML Tool	Proposed System
Claim Submission & Tracking	Yes	No	Yes
Policy Condition Analysis	No	No	Yes
Rejection Prediction	No	Limited	Yes
Explainable Feature Attribution	No	Limited	Yes
Fraud / Anomaly Detection	No	Yes	Yes
Multi-Role Workflow (Patient/Hospital/Admin)	Limited	No	Yes
Bulk Claim Processing	No	No	Yes
Model Analytics Dashboard	No	Limited	Yes

Table 1. Comparison of the Proposed System with Existing Approaches

The proposed system combines claim tracking, policy-condition analysis, explainable rejection prediction and fraud indicators within one multi-role platform, moving beyond point solutions that address only tracking or only fraud detection.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IX Sep 2026- Available at www.ijraset.com

IX. DISCUSSION

Claim rejection rarely has a single cause; it usually results from several interacting policy, clinical, documentation and billing conditions. Instead of returning only an approve/reject label, the proposed system surfaces the individual factors behind each outcome, which is intended to help policyholders correct issues earlier and help administrators focus manual review on the claims that need it most.

The system's current predictive component is a transparent, rule-based scoring engine rather than a trained machine-learning model, and its analytics dashboard displays configured, illustrative metrics rather than experimentally validated ones. This is an appropriate and honest starting point for a prototype: the rule logic is fully inspectable, and the architecture — separating UI, API, evaluation logic and data layer — is designed so a trained model, a real dataset and a persistent database can be introduced later without redesigning the workflow. Because the domain involves sensitive health and financial data, the discussion also treats the system strictly as a decision-support aid, not an autonomous adjudicator, and highlights the need for human oversight, privacy protection and fairness evaluation before any real-world use.

X. CONCLUSION

The Smart Health Insurance Claim Guidance and Rejection Prediction System was developed to make preliminary health-insurance claim assessment more transparent and structured for patients, hospitals and administrators. By combining policy validation, financial and clinical checks, documentation review, fraud indicators and explainable, feature-level predictions within a single role-based platform, the system shows that claim data can be used for more than status tracking — it can help identify, and explain, why a claim may face difficulty. Functional and scenario-based validation confirmed that the implemented decision logic behaves as intended across twelve representative scenarios, providing a solid and extensible foundation for future machine-learning-based enhancement.

XI. FUTURE SCOPE

1) Replace the rule-based engine with a trained Random Forest, XGBoost or LightGBM model on a labelled claims dataset
2) Integrate a larger, real-world insurance dataset for reliable performance evaluation
3) Move from mock/in-memory data and localStorage to a persistent database (MySQL/PostgreSQL)
4) Add OCR-based document processing for scanned policies and medical bills
5) Integrate formal SHAP explainability directly with a trained model
6) Add API latency, throughput and error monitoring
7) Strengthen authentication, access control, encryption and audit logging
8) Deploy via Docker and cloud infrastructure with backups and monitoring
9) Develop a mobile application for claim submission and tracking
10) Add multilingual explanations and a human-in-the-loop review step for borderline claims

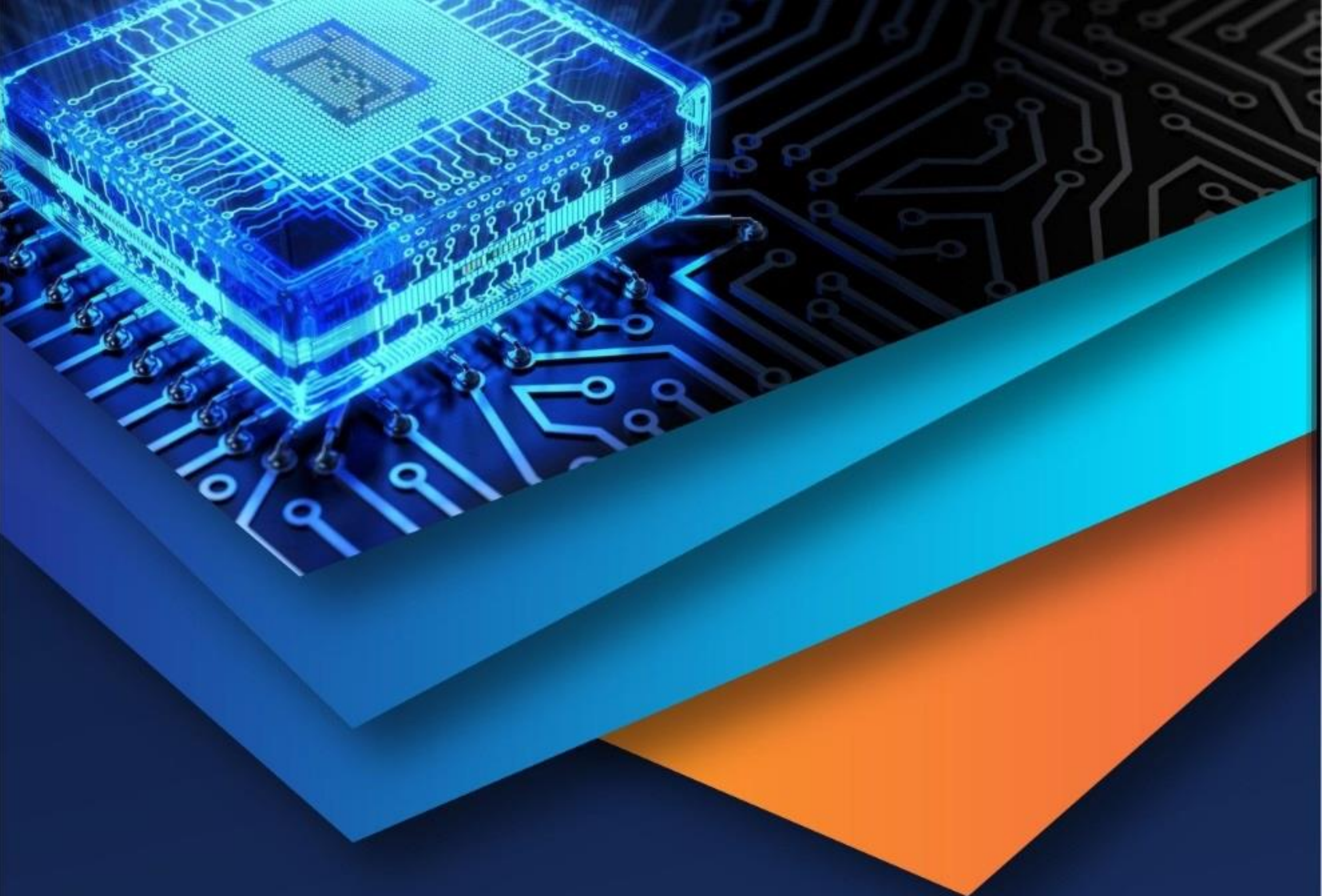
XII. ACKNOWLEDGEMENT

The author sincerely thanks project guide Ms. B. Varshini Priyamvada, Assistant Professor, Department of Computer Applications, for her guidance and support throughout this project, and is grateful to the Department and Aurora Higher Education and Research Academy for the resources and encouragement provided.

REFERENCES

[1] J. M. Johnson and T. M. Khoshgoftaar, "Medicare fraud detection using neural networks," Journal of Big Data, 2019.
[2] K. Kaushik, A. Bhardwaj, A. D. Dwivedi, and R. Singh, "Machine learning-based regression framework to predict health insurance premiums," Int. J. Environ. Res. Public Health, vol. 19, no. 13, p. 7898, 2022.
[3] "Health insurance cost prediction using machine learning," in Proc. 2022 3rd Int. Conf. Emerging Technology (INCET), IEEE, 2022.
[4] E. Nabrawi and A. Alanazi, "Fraud detection in healthcare insurance claims using machine learning," 2023.
[5] J. Debener, V. Heinke, and J. Kriebel, "Detecting insurance fraud using supervised and unsupervised machine learning," J. Risk Insurance, vol. 90, no. 3, pp. 743–768, 2023.
[6] L. Settipalli and G. R. Gangadharan, "WMTDBC: An unsupervised multivariate analysis model for fraud detection in health insurance claims," Expert Syst. Appl., vol. 215, p. 119259, 2023.
[7] J. T. Hancock, R. A. Bauder, H. Wang, and T. M. Khoshgoftaar, "Explainable machine learning models for Medicare fraud detection," J. Big Data, vol. 10, art. 154, 2023.

[8] S. Shekhar, J. Leder-Luis, and L. Akoglu, "Unsupervised machine learning for explainable health care fraud detection," NBER Working Paper No. 30946, 2023.
[9] [9] K. Aarati, A. Shirisha, and K. Bindhu, "Identifying health insurance claim frauds using machine learning concept," J. Sci. Technol., vol. 8, no. 7, pp. 45–57, 2023.
[10] [10] S. D. Permai and K. Herdianto, "Prediction of health insurance claims using logistic regression and XGBoost methods," Procedia Comput. Sci., vol. 227, pp. 1012–1019, 2023.
[11] [11] J. Villegas-Ortega et al., "Methodology for detecting suspicious claims in health insurance using supervised machine learning," Future Internet, vol. 17, no. 12, p. 584, 2025.
[12] [12] S. Kolambe and P. Kaur, "Insurance policy summarization using natural language processing (NLP)," Frontiers Health Inform., vol. 13, no. 3, pp. 4774–4782, 2024.
[13] [13] M. L. Sbodio et al., "Collaborative artificial intelligence system for investigation of healthcare claims compliance," Sci. Rep., vol. 14, art. 11884, 2024.
[14] [14] Muhammad et al., "Fraud detection and explanation in medical claims using GNN architectures," 2025.
[15] [15] D. Li, Z. Jin, L. Qian, and H. Yang, "Textual analysis of insurance claims with large language models," J. Risk Insurance, vol. 92, pp. 505–535, 2025.



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429