DENIAL PREDICTION AND AUTOMATION

Predictive Precision: Minimize Denials, Maximize Revenue, Optimize Outcomes

INTRODUCTION

Predictive Analytics for Healthcare Denial Rates

In this project, we built and validated a **predictive analytics pipeline** to analyze historical healthcare claims data and forecast the likelihood of claim denials for upcoming encounters. This workflow integrates historical denial trends, payer rules, and claim-specific features (such as **CPT codes, ICD codes, and payer rules**) to predict denial risks and help decision-makers address potential issues proactively.

1. We tackle a significant inefficiency in healthcare Revenue Cycle Management (RCM) by addressing the time-intensive process of managing "no response" claims, which **constitute approximately 10-15%** of total claims.
2. These are claims where payers **neither deny nor pay within the standard 30-day timeframe**, requiring analysts to manually gather critical information from payer portals.
3. Through the development of advanced workflows, this project streamlines the process by automating key steps such as determining claim acceptance, payment details (e.g., amount, account, check number), denial reasons, and dates, or the status of claims still in process.
4. By **automating** or structuring this process, we **significantly reduce manual effort,** free up **valuable analyst resources**, and ensure that claims are **seamlessly assigned** to appropriate workflows for resolution.
5. This effort not only **improves** operational efficiency but also positions your organization to **recover revenue faster** and with **greater accuracy**.

MESSAGE FROM APPLICATION CREATOR

1.

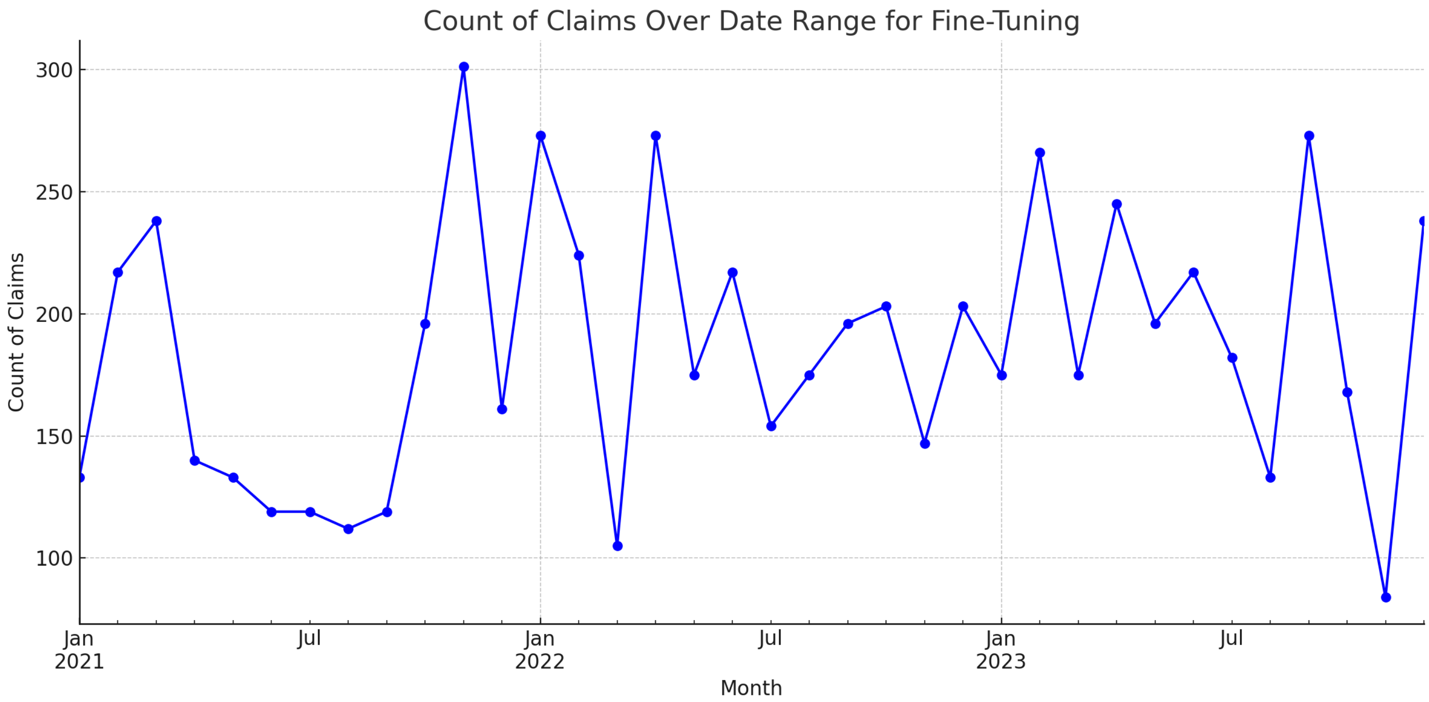
“The MindMeld advanced reasoning model was tuned to run several simulated outcomes. This approach can transform revenue cycle management by utilizing automation and advanced analytics.

- Streamlined claim processes and minimized revenue leakage.
- Faster resolution of "no response" claims through automated workflows.
- Resource optimization by freeing analysts from repetitive tasks, allowing focus on high-value activities.
- Improved accuracy in claim tracking with reduced human error.
- Proactive denial prevention using predictive analytics to identify high-risk claims.
- Accelerated payment recovery through quicker follow-ups.
- Scalable management of claims to handle increased volumes without added administrative burden.

These efficiencies enhance operations and yield significant financial benefits, including faster reimbursements and improved cash flow."- *C. Pete Connor MS- AI/ML*

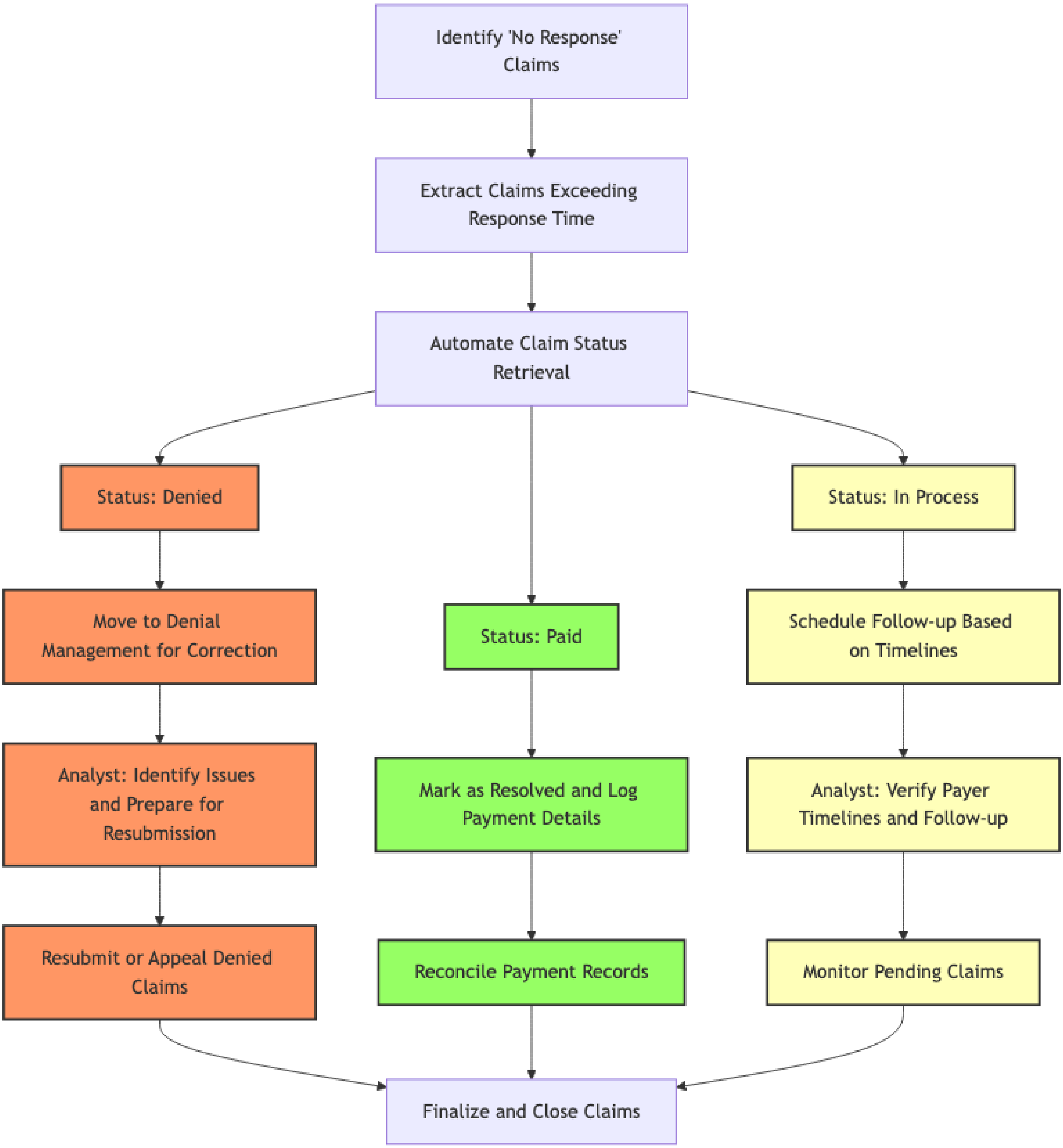
OBJECTIVES

01.	Build Matrix for Predictive Model	Demonstrate strong classification accuracy, effectively distinguishing between denied and paid claims with minimal errors. High precision and recall indicate it predicts denials well, allowing for proactive responses.
02.	Establish Denial Rate Trends	Establish trends where denial rates/reasons vary over time, indicating patterns of high risk. Investigate months with spikes to identify systemic issues, such as policy changes or payer behavior, and implement preventive measures for similar future periods.
03.	Denial Likelihood for Upcoming Encounters	Identify encounters that have a higher likelihood of denial, making them priority cases for review. Alert RCM to review documentation, compliance with payer rules, and any missing pre-authorizations before submission.
04.	Feature Importance from Predictive Model	Certain features like payer rules, CPT codes, and ICD codes significantly impact claim denial predictions. Prioritize these high-impact factors for auditing and compliance to minimize denial risks.
05.	Identify Automation and Improvement	Aid the proof of concept by determining the necessary framework.



The synthesized dataset contains a total of **6,685 claims** spanning the date range from **January 31, 2021**, to **December 31, 2023**.

PROCESSING PATHS AND WORKFLOW AUTOMATIONS



MEASURING PROGRESS

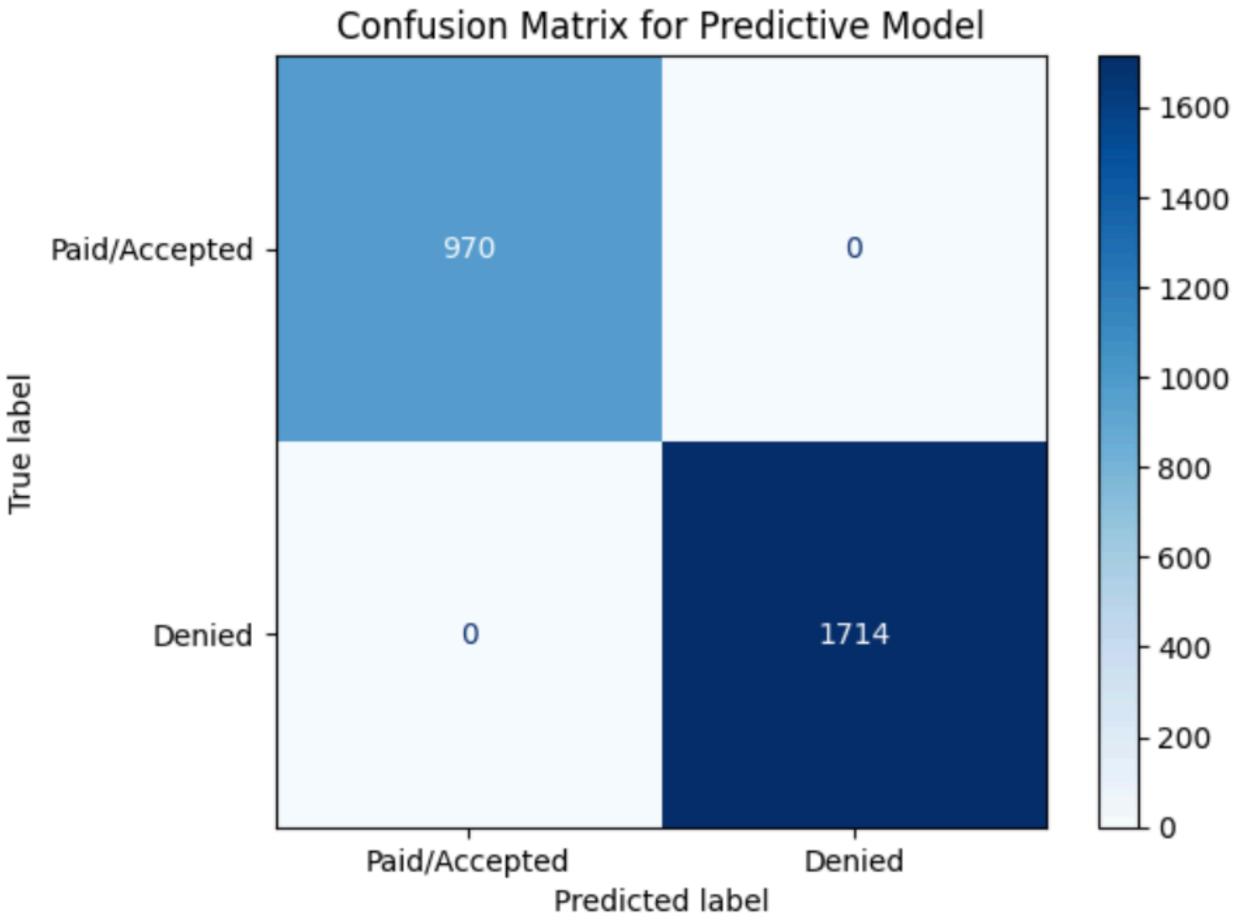
To evaluate the success of this initiative, we will leverage insights from our visual data to establish clear benchmarks and performance metrics. The confusion matrix will be employed to assess the predictive model's precision and recall, ensuring a minimal error rate in classifying denied versus paid claims. We will also monitor trends in denial rates over time to identify and address systemic issues or seasonal fluctuations, implementing targeted interventions to mitigate risks during peak periods.

Additionally, feature importance analysis will support compliance audits by pinpointing the most significant payer rules, CPT codes, and ICD codes, thereby facilitating actionable improvements. The distribution of predicted denial risks will enable efficient resource allocation, prioritizing claims that exceed the high-risk threshold. Finally, we will validate denial likelihood predictions for upcoming encounters by tracking corrective actions taken on high-risk claims and their subsequent resolution outcomes. Collectively, these metrics will foster a data-driven approach to optimizing claims workflows, reducing revenue leakage, and enhancing operational efficiency.

AREA	KEY DATA	OUTCOME
Predicted Denial Risk Distribution	Proportions of claims falling above the high-risk threshold (e.g., >70% predicted denial likelihood) and resolution rates for these claims.	Improved efficiency in resource allocation by prioritizing high-risk claims, leading to quicker resolutions and reduced financial risk.
Denial Likelihood Validation	Number of high-risk claims corrected preemptively and their corresponding resolution outcomes, including approval rates after intervention.	Increased acceptance rates for high-risk claims through effective pre-submission corrections, demonstrating the model's ability to drive actionable improvements.
Confusion Matrix Performance Tracking	Precision, recall, and F1-score metrics for denied and paid/accepted claims, along with the overall classification accuracy.	High values for these metrics (e.g., >90% accuracy) reflect the model's effectiveness in accurately distinguishing denied claims, enabling targeted intervention and reducing misclassification.

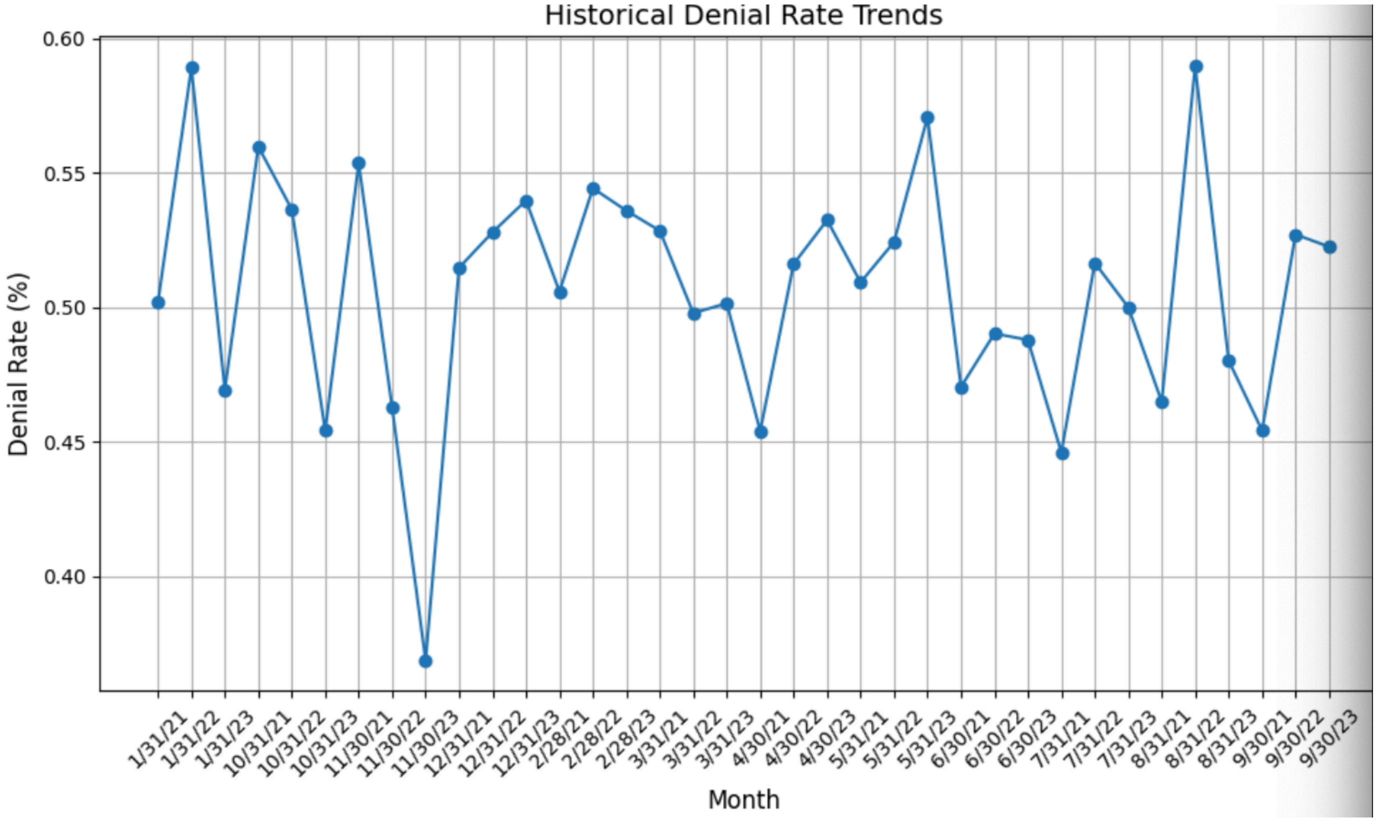
STATISTICS AND OUTCOMES FROM TESTING

RESULTS, INSIGHTS, AND TAKEAWAYS

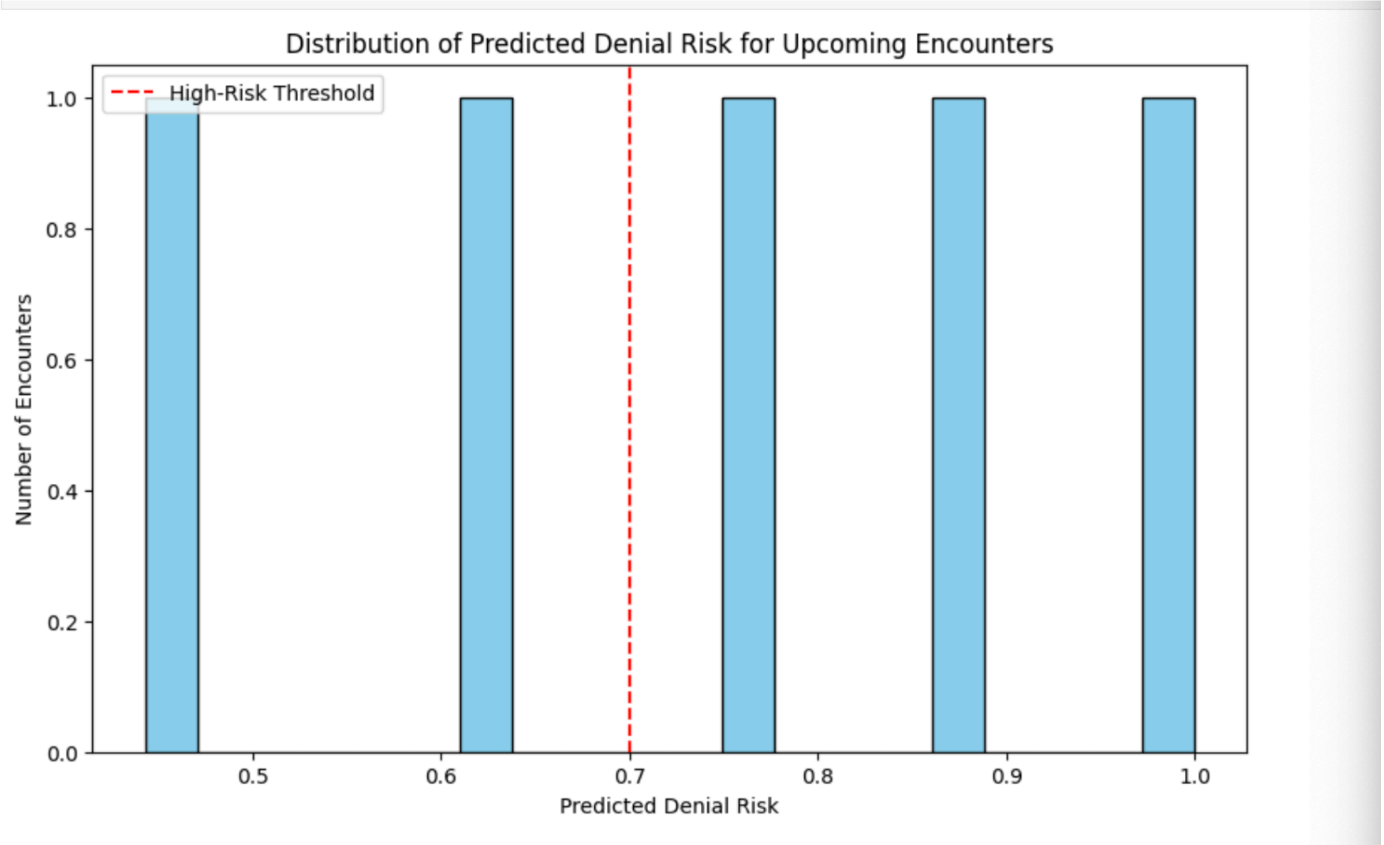


Confusion Matrix for Predictive Model

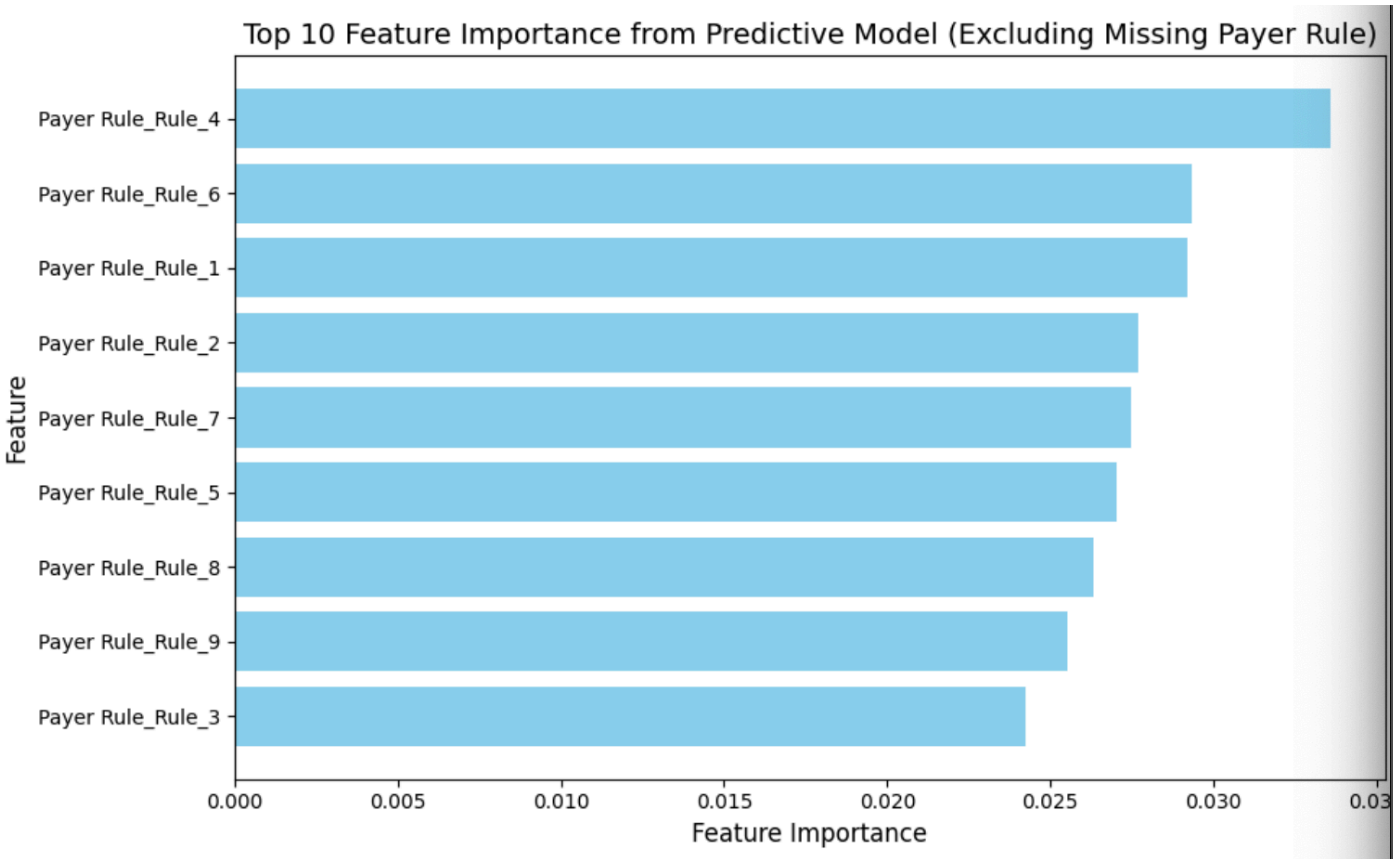
- **Insight:** The model demonstrates excellent classification performance, with minimal errors in distinguishing between denied and paid/accepted claims.
- **Actionable Takeaway:** High precision and recall indicate the model can reliably predict denials, allowing proactive measures to address them.



- **Historical Denial Rate Trends**
- **Insight:** The denial rates fluctuate over time, revealing patterns or periods with high denial risks.
- **Actionable Takeaway:** Focus on investigating months with spikes in denial rates to uncover systemic issues (e.g., policy changes, payer behavior) and implement preventive measures during similar periods.

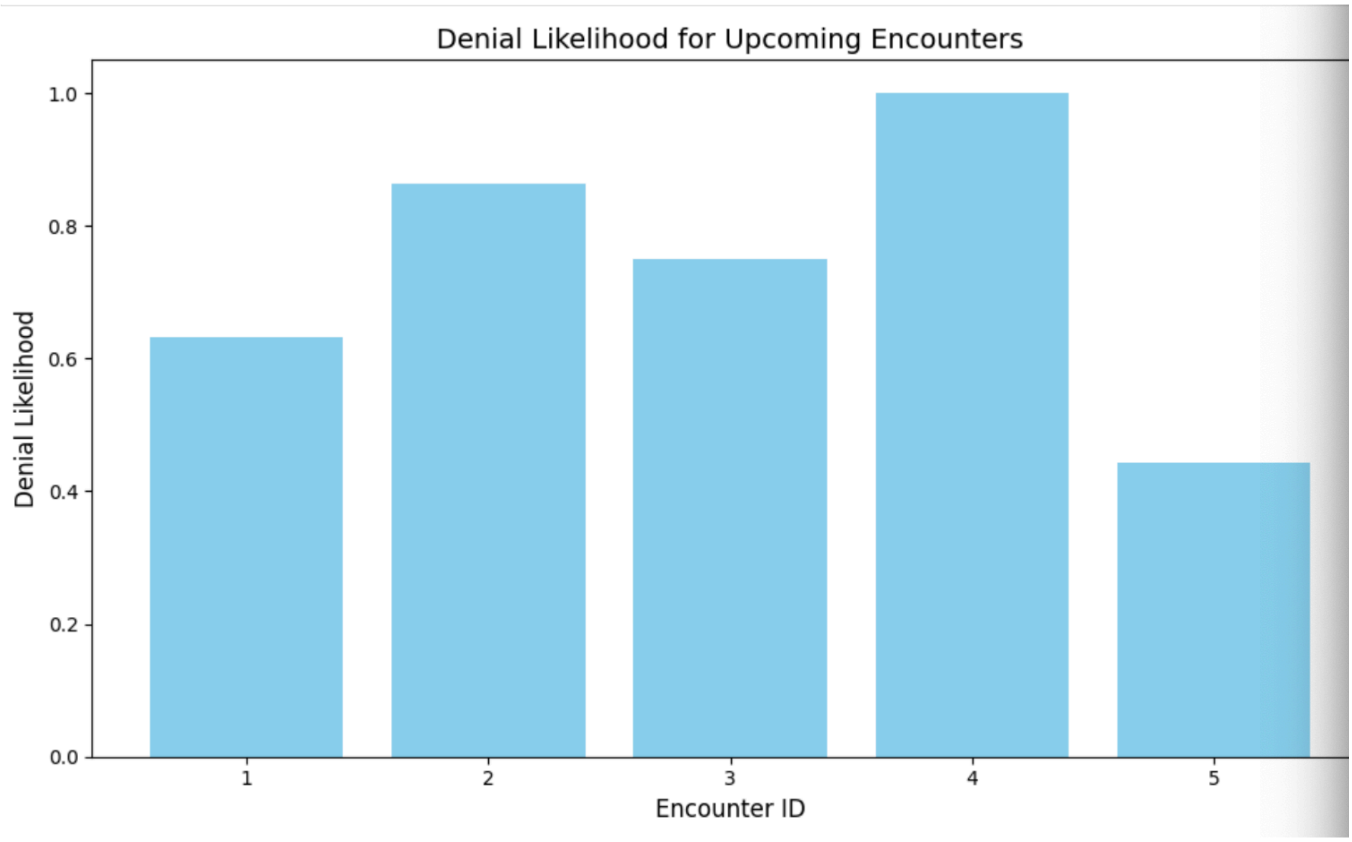


- **Feature Importance from Predictive Model**
- **Insight:** Certain features, such as specific payer rules, CPT codes, and ICD codes, have a greater influence on claim denial predictions.
- **Actionable Takeaway:** Prioritize these high-impact features for auditing and ensuring compliance with payer requirements to reduce denial risks.



Distribution of Predicted Denial Risk

- **Insight:** The distribution shows a range of denial risks, with a clear identification of claims that exceed the high-risk threshold.
- **Actionable Takeaway:** Allocate resources to review and correct claims above the threshold to prevent revenue loss from likely denials.



Denial Likelihood for Upcoming Encounters

- **Insight:** Specific encounters have significantly higher denial likelihoods than others, making them high-priority cases for review.
- **Actionable Takeaway:** Preemptively address these high-risk encounters by verifying documentation, compliance with payer rules, and any missing pre-authorizations before submission.

CONCLUSION

This initiative has demonstrated the transformative potential of leveraging advanced analytics and automation to optimize healthcare Revenue Cycle Management (RCM). By addressing key inefficiencies and proactively managing high-risk claims, we have laid a strong foundation for reducing denial rates, improving resource allocation, and enhancing financial outcomes.

Highlights Review

- **Predictive Model Excellence:** The confusion matrix confirmed the model's reliability in accurately distinguishing between denied and paid claims, enabling targeted corrective actions.
- **Insightful Denial Trends:** Historical denial rate trends revealed actionable patterns, allowing us to mitigate seasonal spikes and systemic issues.
- **Focused Resource Allocation:** Feature importance analysis identified key drivers of denials, ensuring attention is directed where it matters most.
- **Prioritization of High-Risk Claims:** The distribution of predicted denial risks guided efficient resource allocation, expediting the resolution of high-risk cases.
- **Preemptive Claim Corrections:** Denial likelihood predictions for upcoming encounters facilitated proactive adjustments, increasing claim acceptance rates and reducing denials.

ACKNOWLEDGEMENTS

We express our sincere gratitude to all individuals involved in this project for their invaluable time, contributions, and feedback.

Your collaboration and insights have been pivotal in shaping this initiative and steering it toward success.

From sharing expertise to offering constructive criticism, each contribution has refined our approach and ensured that the project's impact aligns with our objectives.

CONTACT INFORMATION

MINDMELD	CPETECONNOR@GMAIL.COM	linkedin.com/in/petecconnor