

Enterprise-Level Emphasis Operational Analytics: Predicting Healthcare Encounter Resolution Success Using Machine Learning

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Abstract

Enterprise-Level Emphasis represents a critical operational framework within healthcare administration, designed to ensure accurate claims processing and encounter data management by systematically identifying and resolving discrepancies. This study analyzed ELE'S operational performance using descriptive statistics and machine learning regression techniques to predict settlement success rates. Performance data from 20 observations revealed robust operational metrics: average claim processing time of 12.17 hours, error rates of 4.16%, employee performance scores of 79.8%, system uptime of 97.61%, and settlement success rates of 91.53%. Correlation analysis showed strong negative relationships between processing time, error rates, and operational outcomes, while there were positive relationships between employee performance, system uptime, and settlement success. Two ensemble learning models—AdaBoost regression and XGBoost regression—were developed to predict settlement success rates. AdaBoost achieved a training R^2 of 0.9993 and a testing R^2 of 0.9548, demonstrating reasonable generalization despite moderate overfitting. XGBoost showed severe overfitting with perfect training performance ($R^2 = 1.0000$) but poor testing results ($R^2 = 0.8907$), which reduced the performance of AdaBoost on unobserved data. This analysis confirms the operational performance of ELE, while highlighting the importance of model regularization in predictive analyses. The high generalization of AdaBoost makes ELE more suitable for predicting resolution outcomes, although hyperparameter optimization could improve the practical applicability of the two models in healthcare operational management.

Key words: Claims Processing, Healthcare Analytics, Adaboost Regression, XGboost Regression, Predictive Modeling, Operational Efficiency

Introduction

Enterprise-Level Emphasis, commonly known as ELE, is a key component of Humana's healthcare administration infrastructure designed to address one of the most persistent challenges in the health insurance industry – accurate claims processing and encounter data management.[1] At its core, ELE serves as a specialized operational framework that identifies, investigates, and resolves discrepancies in healthcare encounter records, ensuring that both providers and members receive appropriate reimbursement and coverage while complying with regulatory requirements. The foundation of ELE'S operations lies in its systematic approach to encounter data verification. [2] Healthcare encounters encompass every interaction between patients and healthcare providers, from routine office visits to complex surgical procedures and ongoing chronic care management. Each encounter generates a vast amount of data that must be accurately captured, coded, and processed through insurance systems. When discrepancies arise due to coding errors, incomplete documentation, duplicate submissions, or system processing issues – ELE teams efficiently investigate and take action to resolve these matters. [3] This proactive approach prevents payment delays, reduces

claim denials, and reduces the administrative burden on healthcare providers who partner with Humana. ELE'S operating model combines advanced analytics with human expertise to create a comprehensive resolution process. Sophisticated algorithms and data-processing tools scan millions of appointment records and identify patterns that suggest errors or discrepancies.

These include mismatched diagnosis and procedure codes, appointments submitted for the wrong service categories, time discrepancies, or authorization issues. [4] Once flagged, these cases are routed to specialized resolution teams with in-depth knowledge of medical coding standards, CMS guidelines, and Humana's specific processing requirements. These experts work directly with provider offices, reviewing medical documents, and making necessary corrections to ensure appointments are processed accurately and efficiently. [5] ELE'S importance extends beyond simple claims processing to the areas of risk adjustment and quality measurement, critical components of modern health care financing. Under Medicare Advantage and other value-based care models, accurate encounter data directly impacts health plan risk scores and quality ratings. Incomplete or inaccurate encounter records can have significant financial consequences for both health plans and providers, potentially impacting millions of dollars in revenue adjustments.[6] ELE teams work diligently to ensure that chronic conditions are properly documented and coded, preventive services are accurately captured, and quality measures are appropriately reflected in encounter submissions. This attention to detail helps Humana maintain accurate risk profiles for its member populations while ensuring that providers receive appropriate reimbursement for the complexity of the care they provide. [7] From a provider perspective, ELE serves as a valuable partnership resource that reduces administrative friction and improves revenue cycle efficiency. Healthcare organizations often struggle with the complexity of insurance requirements, coding updates, and documentation standards that vary across payers. [8] ELE'S outreach efforts include educational efforts to help

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provider staff understand common submission errors, stay up-to-date with coding changes, and implement best practices for meeting documentation. By proactively identifying and communicating procedural issues before they lead to widespread denials, ELE helps providers maintain stable cash flow and reduce costly rework associated with claims revisions.[9] The operational efficiency that ELE brings to Humana's business operations cannot be overstated. In an industry where processing delays and errors can be mixed with member satisfaction issues, provider relationship issues, and regulatory scrutiny, having a dedicated remediation operation creates consistency and predictability. [10] Members benefit from fewer coverage gaps and billing disputes, providers enjoy smoother reimbursement processes, and Humana maintains strong relationships with both constituencies while ensuring compliance with federal and state regulations. Looking ahead, ELE continues to evolve with technological advances in healthcare management. [11] Artificial intelligence and machine learning capabilities are increasingly being integrated into the appointment verification process, enabling more predictive analytics that can identify issues more quickly and prevent errors before they are submitted. Real-time claim correction tools, improved provider portals, and automated feedback systems are all part of ELE'S modernization efforts, designed to create a more seamless appointment management experience. [11] As healthcare continues its transformation toward value-based care models where accurate data will become even more critical to success, operations like ELE will be essential infrastructure, ensuring that the complex machinery of healthcare financing operates smoothly, fairly, and efficiently for all stakeholders involved in the care delivery ecosystem. [12].

Materials and Method

The data presented reveals key performance metrics across multiple dimensions of claims processing operations. Claims processing volumes range from 9,500 to 15,600 claims, indicating variation in workload distribution across different time periods or groups. This fluctuation indicates that the operation is handling a variety of processing demands, requiring flexible staffing and resource allocation to maintain consistent service levels. Error rates across all entries range from 3,000 to 5,800, demonstrating robust quality control mechanisms. These minimum error rates are critical to maintaining provider satisfaction and reducing costly rework. Consistency in keeping errors within this narrow range suggests standardized procedures and effective training protocols that help ensure accurate claims processing despite varying staff sizes. Employee performance metrics ranging from 74,000 to 85,000 generally indicate strong productivity levels, although the variation suggests opportunities to identify and replicate best practices from high-performing groups. System uptime figures are exceptionally strong, consistently above 96,000 and often reaching 98,700, reflecting a reliable technology infrastructure that minimizes processing disruptions. Resolution rates show excellent performance, with most entries between 86,800 and 95,300.

These high-resolution rates indicate that the majority of claims are processed successfully without the need for escalation or extended investigation. Collectively, the data suggests a well-functioning operation that balances scale, accuracy, efficiency and system reliability to deliver consistent results in claims processing. AdaBoost regression and XGBoost regression represent two powerful ensemble learning techniques that have revolutionized predictive modeling in machine learning. AdaBoost, short for adaptive boosting, works by sequentially training weak learners - typically simple decision trees - where each subsequent model focuses on correcting errors made by its predecessors. The algorithm assigns weights to training instances, increasing the weights for observations that previous models predicted poorly, thereby forcing new models to focus on difficult instances. This iterative refinement process continues until the final

predictions are generated by a weighted vote of all weak learners, until a certain number of models have been generated, or until an acceptable accuracy is achieved. XGBoost, or Extreme Gradient Boosting, extends the principles of gradient boosting with significant computational and performance improvements. It builds trees in a sequential manner similar to AdaBoost, but uses gradient descent optimization to reduce the loss functions more efficiently. XGBoost incorporates regularization techniques to prevent overfitting, automatically handles missing values, and enables parallel processing for fast computation. Its sophisticated tree-pruning algorithms and built-in cross-validation capabilities make it exceptionally robust for complex datasets. While AdaBoost excels in simplicity and interpretability, XGBoost generally outperforms it in accuracy, speed, and scalability for large datasets. XGBoost's advanced features—including customizable objective functions, early stopping, and feature importance metrics—have made it a preferred choice for competitive machine learning applications and real-world regression problems that require high predictive accuracy.

Analysis and Discussion

Table 1. Enterprise-Level Emphasis Descriptive Statistics

	Claim Processing Time (hrs)	Error Rate (%)	Staff Efficiency Score	System Uptime (%)	Resolution Success Rate (%)
count	20.0000	20.0000	20.0000	20.0000	20.0000
mean	12.1700	4.1550	79.8000	97.6050	91.5250
std	1.9703	0.8438	3.2379	0.7395	2.6559
min	9.5000	3.0000	74.0000	96.2000	86.8000
25%	10.4250	3.3750	77.7500	97.0750	89.6750
50%	12.0000	4.0500	80.0000	97.6500	91.9500
75%	13.6500	4.8250	82.2500	98.2250	93.9500
max	15.6000	5.6000	85.0000	98.7000	95.3000

Descriptive statistics for Enterprise-Level Emphasis reveal consistently strong performance across all dimensions measured. Based on 20 observations, the average claim processing time is 12.17 hours, with relatively low variability (standard deviation of 1.97), indicating predictable turnaround times ranging from 9.5 to 15.6 hours. The average processing time of 12 hours indicates a uniform workflow distribution. Error rates are impressively low, averaging only 4.16% with minimal spread (0.84 standard deviation), indicating strong quality control. The operation consistently delivers accurate processing, with three-quarters of observations maintaining error rates below 4.83%. Employee performance scores average 79.8 out of 100, with half of the observations exceeding 80.0, reflecting solid productivity, although there is room for improvement with the highest score achieved being 85.0. System uptime statistics are exceptional, averaging 97.61%, with significant tight clustering around the mean (0.74 standard deviation), ensuring a reliable technical infrastructure. Resolution success rates are equally impressive, averaging 91.53%, with 75% of cases achieving at least 93.95% resolution, indicating that the operation effectively completes most encounters without escalation. Overall, these metrics paint a picture of a well-functioning, reliable operation with strong performance metrics and consistent service delivery.

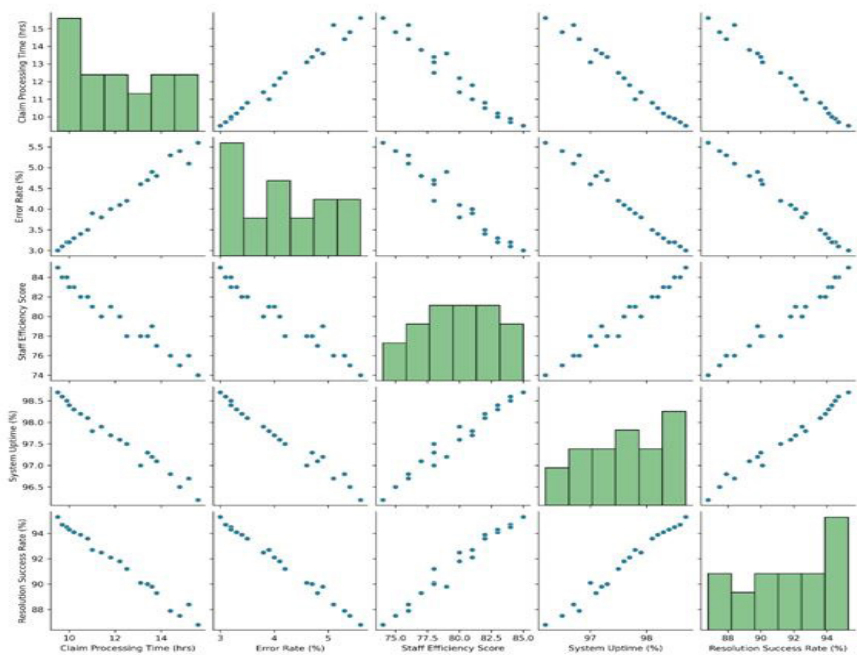


Figure 1: Enterprise-Level Emphasis Effect of Process Parameters

The scatterplot matrix reveals important relationships between operational variables. Strong negative correlations are evident between claim processing time and resolution success rate, indicating faster processing partners with better outcomes. Error rates show clear inverse relationships with staff efficiency, system uptime, and resolution success, confirming that quality control directly impacts performance. Staff efficiency shows positive correlations with system uptime and resolution rates, indicating that well-trained staff are using technology effectively. The distribution histograms reveal relatively normal distributions for most variables, although error rates and system uptime show slight skew. Significant clustering patterns in the scatterplots indicate operational sweet spots where multiple favorable conditions converge. Tight linear patterns between multiple variable pairs suggest predictable, systematic relationships that can inform process strategies and predictive modeling efforts for ELE operations.



Figure 2: Enterprise-Level Emphasis Correlation heatmap

The correlation heat map measures very strong linear relationships between all operational metrics. Claim processing time and error rate exhibit a nearly perfect positive correlation (0.99), indicating that longer processing times are consistently associated with higher error rates, which may reflect complex case difficulty. Both variables show strong negative correlations (-0.98 to -1.0) with staff performance, system uptime, and resolution success rates, confirming that delays and errors are severely hindering performance. Conversely, staff performance, system uptime, and resolution success demonstrate strong positive correlations (0.98-0.99), indicating that these metrics move together as indicators of operational health. Consistently high correlation levels indicate tight linkages between all performance dimensions, with improvements in any single area likely to be positively cascading across the operation. These relationships support the use of these metrics collectively for predictive modeling and suggest that addressing processing time and error rates simultaneously can yield substantial improvements in all performance indicators.

Table 2. AdaBoost Regression Resolution Success Rate (%) Train and Test performance metrics

Model	Data	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
AdaBoost Regression	Train	0.9993	0.9994	0.0048	0.0694	0.0278	0.2000	0.0000	0.0000
	Test	0.9548	0.9740	0.2688	0.5184	0.4625	0.9000	0.0000	0.4500

The AdaBoost regression model shows exceptional performance on the training data, but shows significant degradation on the test data, indicating possible overfitting. On the training set, the model achieves a nearly perfect fit with an R^2 of 0.9993, which explains 99.93% of the variance in the resolution hit rates. The very low error metrics – an RMSE of 0.0694 and an MAE of 0.0278 – indicate that the model has essentially memorized the training patterns with minimal prediction error. However, the test performance exhibits significant discrepancies. The R^2 of 0.9548 is robust, explaining 95.48% of the variance, which is a significant decrease from the training performance. The RMSE increases dramatically to 0.5184, and the MAE rises to 0.4625, representing almost half a percentage point in the data where prediction errors are not observed. While the training data is only 0.2, the maximum error on the test data reaches 0.9, indicating that the model is struggling with some outliers. The average absolute error of 0.45 on the test data, compared to essentially zero on the training data, further confirms the overfitting concerns. Despite these gaps, the model's test R^2 is above 0.95, indicating that it still provides valuable predictive power for solution success rates, although regularization techniques or ensemble methods could improve generalization performance.

Predicted vs Actual Resolution Success Rate (%) (Training data)

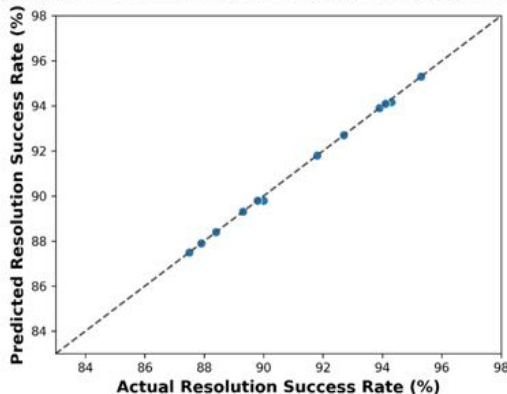


Figure 3: AdaBoost Regression Resolution Success Rate (%) Training

The AdaBoost training predictions show a nearly perfect model fit, with all predicted values falling almost exactly on the diagonal reference line that represents correct predictions. The points are tightly clustered around the ideal prediction line over the entire range of true resolution success rates, from approximately 87% to 95%. The minimal deviation from the diagonal indicates that the model has learned the training patterns with exceptional accuracy, achieving a reported R^2 of 0.9993. The consistent fit quality across different success rate levels indicates that the model handles low- and high-performing cases equally well, without any systematic bias. However, this nearly flawless training performance, while impressive, raises concerns about potential overfitting. The absence of any meaningful prediction error suggests that the model may have memorized the training data rather than learned common patterns, which is evident when compared to the experimental performance where prediction errors increase significantly.

Predicted vs Actual Resolution Success Rate (%) (Testing data)

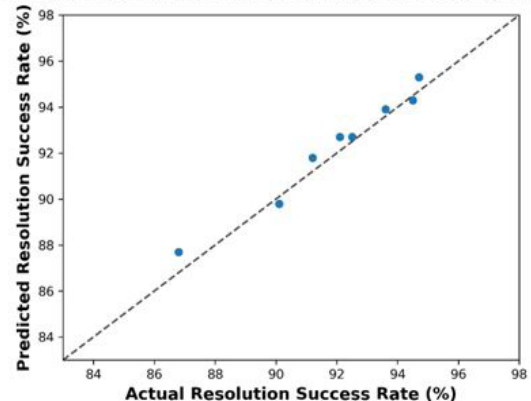


Figure 4: AdaBoost Regression Resolution Success Rate (%) Testing

The AdaBoost test predictions exhibit moderate degradation from training performance, but maintain reasonable predictive accuracy. Most of the points cluster near the diagonal reference line, although there is a significantly higher scatter compared to the training data. The predictions are well correlated with the true values in the 87% to 95% hit rate range, consistent with the reported test R^2 of 0.9548. However, several points deviate from the ideal line, especially in the middle range around 90-92%, indicating that the model struggles with some events not observed during training. The maximum vertical deviation appears to be less than one percentage point for most predictions, consistent with the reported MAE of 0.4625. While the prediction quality decreases from training, the overall pattern indicates that the model captures meaningful relationships and provides useful predictions. AdaBoost demonstrates learning common patterns despite overfitting concerns, making it reasonably reliable for predicting resolution success rates on new ELE operational data.

Table 3. XGBoost Regression Resolution Success Rate (%) Train and Test performance metrics

Model	Data	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
XGBoost Regression	Train	1.0000	1.0000	0.0000	0.0005	0.0003	0.0012	0.0000	0.0001
	Test	0.8907	0.9698	0.6504	0.8065	0.6860	1.6946	0.0001	0.5993

The XGBoost regression model exhibits severe overfitting, achieving perfect training performance but significantly weaker test results. On the training data, the model exhibits a perfect fit with an R^2 of 1.0000 and near-zero error metrics - 0.0005 RMSE and 0.0003 MAE - indicating complete memorization of the training patterns with no meaningful error tolerance. The test performance exhibits a dramatic decline, with R^2 dropping to 0.8907, explaining only 89.07% of the variance compared to the perfect training fit. The RMSE increases to 0.8065 and MAE to 0.6860, indicating prediction errors averaging 0.7 percentage points in the unobserved data. The maximum error of 1.6946 on the test data compared to 0.0012 on the training data demonstrates the model's inability to generalize to new instances. Compared to AdaBoost (Table 2), XGBoost actually did not perform better on the test data despite its better training performance. It achieved a test R^2 of 0.9548 compared to AdaBoost's 0.8907, and a lower test RMSE (0.5184 vs 0.8065). This indicates that XGBoost's default hyperparameters are not sufficiently regularized for this dataset. The model requires tuning to prevent overfitting and improve its generalization ability to predict resolution hit rates - either by reducing the learning rate, increasing the regularization parameters, or limiting the tree depth.

Predicted vs Actual Resolution Success Rate (%) (Training data)

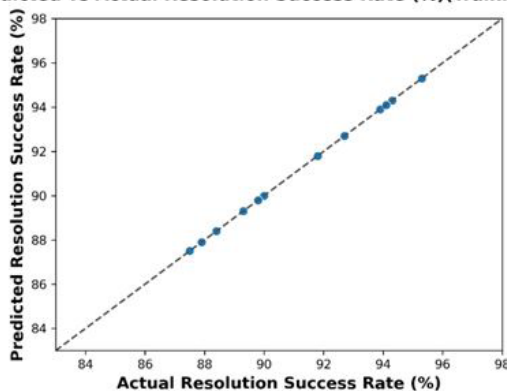


Figure 5: XGBoost Regression Resolution Success Rate (%) Training

The XGBoost training predictions show perfect model fit, with all points positioned precisely on the diagonal reference line without any visible deviation. The predictions cover the entire range of true resolution hit rates from approximately 87% to 95%, demonstrating flawless accuracy at all performance levels. This perfect alignment reflects an R^2 of 1.0000 and nearly zero error metrics (RMSE of 0.0005). The complete absence of prediction error indicates that the model has achieved total memorization of the training patterns, capturing every nuance with no residual variation. While this demonstrates the powerful learning ability of XGBoost, the perfect fit is a clear warning sign of severe overfitting. The model has learned not only the underlying patterns, but also random noise and idiosyncrasies specific to the training data, which prevents it from generalizing to new cases, as demonstrated by significantly degraded experimental performance.

Predicted vs Actual Resolution Success Rate (%) (Testing data)

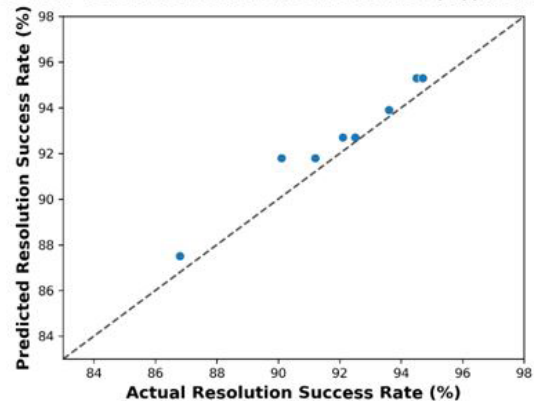


Figure 6: XGBoost Regression Resolution Success Rate (%) Testing

The XGBoost experimental predictions exhibit a significant decline from the training performance, with considerable scatter around the diagonal reference line. While the points generally trend along the best prediction line, several deviate significantly, notably an outlier approaching 87% true predicted at 87.5%, and several points in the 91-93% range exhibit significant prediction errors. The spread of the points indicates a prediction uncertainty of approximately 1-2 percentage points for many cases, consistent with the reported experimental RMSE of 0.8065 and MAE of 0.6860. Compared to the experimental performance of AdaBoost, XGBoost exhibits inferior generalization despite the excellent training fit. The clustering method indicates that the model performs reasonably well for medium-sized hit rates, but struggles with edge cases. This dramatic gap between correct training and moderate test performance confirms severe overfitting, which suggests that hyperparameter tuning for XGBoost - reducing complexity, increasing regularization - improves generalization, and achieves practical predictive value for ELE functions.

Conclusion

This comprehensive analysis of Enterprise-Level Emphasis demonstrates the critical role of proper encounter data management in modern healthcare management. ELE'S performance metrics reveal a well-functioning architecture with predictable processing times, low error rates, high system reliability, and an average resolution success rate of 91.53%. The strong correlations identified between operational variables

confirm that improvements in processing efficiency and error reduction stack are positive across all performance dimensions, validating ELE'S integrated approach to claims resolution. A comparative evaluation of AdaBoost and XGBoost regression models provides valuable insights into predictive modeling for healthcare operations. While both algorithms demonstrate powerful learning capabilities on training data, AdaBoost proved superior for practical applications, achieving a test R^2 of 0.9548 compared to XGBoost's 0.8907. XGBoost's excellent training performance

and significant test decay highlight the severe overfitting issues that require hyperparameter tuning to achieve reliable generalization—including reduced learning rates, increased regularization, and limited tree depth. The findings emphasize that operational excellence in healthcare encounter solutions requires both robust procedural frameworks and sophisticated analytical capabilities. ELE'S success stems from combining human expertise with advanced technology, while predictive modeling improves decision-making by accurately predicting solution outcomes. Future optimization should focus on implementing disciplined machine learning models, expanding real-time analytics capabilities, and using artificial intelligence to proactively prevent errors. As healthcare continues to shift toward value-based care models where data accuracy directly impacts financial performance, operations like ELE, supported by validated predictive models, will be essential infrastructure that ensures efficient, accurate, and compliant healthcare financing for all stakeholders.

Conclusion

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