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An Integrated Learning-Based Model for Intelligent Classification of Logistics Claims Risk and Prediction of Payout Amounts

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Abstract

In recent years, the rapid development of the express and logistics industry has led to a continuous increase in shipment volume, accompanied by a growing number of claims disputes and payment risks. The intelligent automation of the claims settlement process has become a crucial direction for enterprises to reduce costs and improve efficiency. For Problem 1, this paper proposes a claims risk labeling model based on quantile distribution analysis and monotonicity constraints. The method employs a combined strategy of equal-frequency binning, quantile estimation, PAVA monotonic regression, and PCHIP continuous interpolation to ensure the classification boundaries are smooth and align with business logic. The results show that the proportions for the three classified risk groups are: Reasonable Claims at 85.12%, Elevated Claims at 12.19%, and Severe Overclaims at 2.70%. To address problem 2, this paper proposes a Stacking ensemble learning-based model for predicting the actual claim payment amount in logistics compensation. By performing feature selection, enhanced feature engineering, and target variable transformation on historical waybill data, we employed multiple machine learning algorithms, including CatBoost, MLP neural networks, XGBoost, and LightGBM, and combined them using a Stacking ensemble strategy to optimize prediction performance. For problem 3, this paper proposes a risk labeling classification model based on an MLP model to determine the risk level category of shipping orders. To address the severe class imbalance in the dataset, the SMOTE oversampling method was employed to balance the sample distribution. At the model level, a CatBoost classifier, a neural network (MLP), and a Support Vector Machine (SVM) were trained separately, and their performance was compared via cross-validation. The results indicate that the MLP model performed best, achieving a weighted F1-Score of 0.9098 and a training accuracy of 95.55%, significantly outperforming CatBoost and SVM. This demonstrates the model's strong discriminative capability.

Keywords

logistics claims risk identification, stacking ensemble learning, MLP model, classification evaluation

1. Introduction

In the ongoing development and refinement of logistics services, logistics companies have prioritized customer service optimization and experience enhancement as core strategic issues. During the fulfillment process, uncontrollable risk events such as package loss or damage are difficult to completely avoid, making claims service a critical component of a logistics company's operational system. Effective claims management serves not only as a vital tool for companies to restore customer relationships and build brand credibility, but also as a core support for balancing service quality with operational costs and ensuring the company's sustainable development. Claims service is typically divided into pre-sales and post-sales components. The pre-sales phase aims to identify risks in advance and recommend corresponding logistics services to customers. The post-sales phase focuses on controlling claims costs, aiming to reduce instances of excessive payouts while ensuring reasonable claim settlements. Therefore, using the discrepancy data from claim payouts to flag shipments for which customers have submitted claims has become a crucial method for predicting the risk level of shipment claims.

2. Model Establishment and Solution

2.1 Conditional Quantile Model Based on PAVA Monotonic Constraints

Based on the requirements that reasonable claims account for no less than 85% and severely excessive claims account for less than 3%, we have designed the following basic percentile thresholds:

$$TH = \begin{cases} 85\%, Reasonable\ request/Excessive\ demand \\ 97\%, Demands\ are\ excessive/Significantly\ over\ the\ top \end{cases} \tag{1}$$

From a practical business perspective, we consider that as the claim amount M increases, the permissible fluctuation in the reasonable claim difference should also widen. This reflects the logic that larger amounts warrant greater tolerance for reasonable discrepancies.

$$\min_{\widehat{th}_1^{dk} \le \cdots \le \widehat{th}_K^{dk}} \sum_{i=1}^{K} w_i \left(th_i^{dk} - \widehat{th}_i^{dk} \right) \tag{2}$$

When adjacent data blocks—in our case, the quantile sequences within box plots—fail to satisfy the non-decreasing constraint, merge the two box plot blocks. The quantiles of the new block are the weighted average of the two blocks:

$$TH_{merged} = \frac{w_i th_i^{dp} + w_{i+1} th_{i+1}^{dp}}{w_i + w_{i+1}} \tag{3}$$

The weight of the new box model block is the sum of the weights of the box models before merging:

$$w_{merged} = w_k + w_{k+1} \tag{4}$$

Repeat the merging operation until the quantile sequences formed by all quantiles within the box model blocks satisfy the non-decreasing constraint $th_1^{dk} \le \cdots \le th_n^{dk}$, where n is the final number of box models.

2.2 PCHIP-Based Interpolation Regression Model

Given that actual claim amounts in real-world data exhibit a continuous distribution, we employ piecewise cubic Hermite interpolation polynomials (PCHIP) for value-preserving interpolation.

For a discrete quantile threshold sequence$(x_1, th_1^{dp}), (x_2, th_2^{dp}), \cdots (x_n, th_2^{dp})$, where n denotes the number of box models after PAVA monotonic processing, and x_i represents the midpoint of each box model. The interpolation polynomial over [x_i, x_(i+1)] is constructed as follows:

$$k_0(t) = t^3 - 2t^2 + t, k_1(t) = t^3 - t^2 \tag{5}$$

Among these, α_i, α_{i+1}represent the derivative values at nodesx_i, x_{i+1}. First, define $d_i = \frac{th_{i+1}^{dp} - th_i^{dp}}{x_{i+1} - x_i}$. Then, $\alpha_i$is calculated using the following formula:

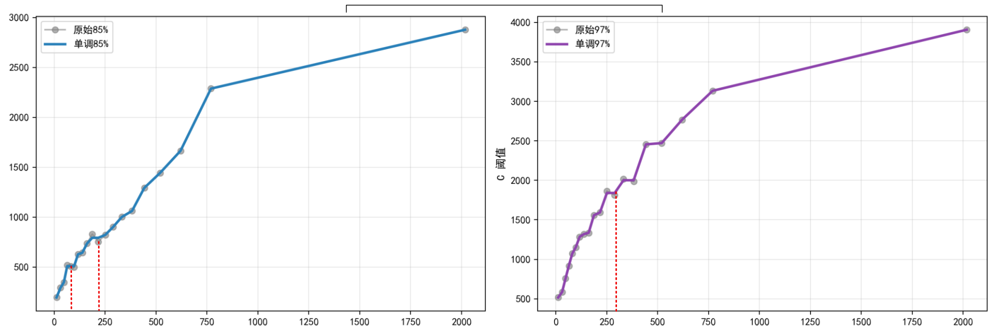
$$m_i = \begin{cases} \frac{2d_{i-1}d_i}{d_{i-1}+d_i}, d_i same\ as\ d_{i-1} \\ 0,\ d_i not\ same\ as\ d_{i-1} \end{cases} \tag{6}$$

Through PCHIP interpolation, the quantile threshold sequence is expanded from a discrete to a continuous sequence while preserving the monotonicity of the quantile sequence. This provides a continuous assessment criterion for subsequent three-category labeling (reasonable demand / excessive demand / severely excessive demand).

2.3 Analysis of Experimental Results

After binning, PAVA monotonicity constraints are applied to ensure the quantile thresholds satisfy the condition of monotonic non-decreasingness.

Figure 1: Monotonicization of quantiles



Through monotonicity processing, both the 85th and 97th percentile thresholds achieved stable monotonic increasing trends. Following PCHIP interpolation and linear regression fitting, the quantile threshold changes depicted in the figure below were obtained, and the data was classified accordingly:

It can be seen that reasonable claims account for 85.1%, while excessively high claims make up 2.7%, meeting the target requirements. It can be observed that the reasonable claims curve remains the most stable overall, showing a slight decline as the M-box center increases but consistently staying at a high level.

3. Model Development and Solution

The actual claim amount is a critical parameter for calculating claim differences. Accurately predicting this value is vital for corporate financial planning and risk control. However, its determination involves multiple factors, exhibiting characteristics of non-linearity, multi-coupling, and non-linear relationships. In this study, we first employ feature selection to identify the most relevant characteristics for predicting actual claim amounts.

3.1 Feature Selection

3.1.1 Continuous Feature Selection Based on Pearson Correlation Coefficients

In the given dataset, there are 24 features beyond the actual claim amount. A large number of irrelevant and redundant features can interfere with the model's learning of core patterns, leading to overfitting and increasing computational costs.

Represent the data as $Y = (X_1, \cdots X_N)$, where N = 25 denotes 25 dimensional features including risk-labeled features. Use Equation (3-1) to calculate the correlation between the 25 features (excluding the actual claim amount) and the actual claim amount.

$$r = \frac{Cov(X,M)}{\sigma_X \sigma_M} = \frac{\sum_{i=1}^{n-1}(X_i - \overline{M})(M_i - \overline{M})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(M_i - \overline{M})^2}} \tag{7}$$

For categorical variables, we convert them into binary numerical vectors using one-hot encoding. Additionally, for claim amounts $S = (s_1, \cdots s_n)$, where a minority of data points represent large amounts while the majority represent small amounts, we apply a logarithmic transformation:

$$\overline{s_i} = log(1 + s_i) \tag{8}$$

After processing, the original data is obtained through the inverse transform:

$$s_i = e^{\overline{s_i}} - 1 \tag{9}$$

3.1.2 ANOVA-Based Feature Selection for Classification

For categorical variables, such as risk classification categories or anomaly causes, the ANOVA method is employed to assess the ability to analyze distribution differences between categories:

$$SSW = \sum_{i=1}^{k}\sum_{j=1}^{n_i}\left(x_{ij} - \overline{M_i}\right)^2 \tag{10}$$

Where x_i is the categorical variable, n_i is the sample size within that category, x_{ij} is the jth sample in category i, $\overline{M}$is the overall mean of continuous variables, and $\overline{M_i}$ is the mean of continuous variables within category i:

$$SST = SSB + SSW \tag{11}$$

Use the F-statistic for observation:

$$F = \frac{MSB}{MSW} \tag{12}$$

Among these, $MSB = \frac{SSB}{k-1}$ represents the between-group mean square, while $MSW = \frac{SSW}{n-k}$ denotes the within-group mean square.

3.2 Practical Method for Predicting Actual Claims Amounts Based on Stacking Ensemble Learning

Stacking integrated learning operates through a two-layer model collaboration: first, multiple base models learn data features and output predictions; then, a meta-model integrates these predictions to generate a more accurate final prediction. The meta-models used are listed below.

3.2.1 MLP Neural Network Prediction Model

The MLP neural network is a type of neural network that integrates stacked fully connected layers with backpropagation of errors. From the input layer to the first hidden layer: The input to the j th neuron is $z_2^j = \sum_{i=1}^{100} w_{2,ji}a_1^i + b_2^j$.After passing through the ReLU activation function, the output of the second hidden layer.

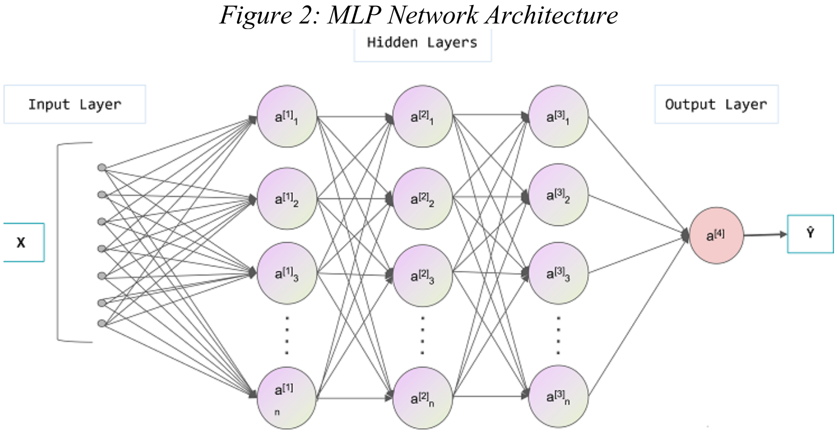
$$L = \frac{1}{n}\sum_{i=1}^{n}\left(M_i - \widehat{M_i}\right) \tag{13}$$

Where M_i is the actual claim amount in the training set, and$\widehat{M_i}$is the predicted actual claim amount. In the backpropagation network, parameters are optimized through iterative error backpropagation:

$$W^l = W^l - \eta \nabla_{W^l} L$$
$$b^l = b^l - \eta \nabla_{b^l} L \tag{14}$$

The learning rateη, $\nabla_{W^l}L, \nabla_{b^l}L$ is the gradient of the loss function$L$withW^landb^lrespect to the sum.

Figure 2: MLP Network Architecture



Through the multi-layer hidden layers and activation functions of the backpropagation neural network, complex nonlinear interactions between features can be captured, as illustrated in the structural diagram above. However, this approach carries the risk of overfitting.

3.2.2 Predictive Model for Extreme Gradient Boosting

Extreme Gradient Boosting (XGBoost) is an efficient ensemble learning algorithm based on gradient boosting decision trees. The prediction value at iteration t is composed of the sum of the predictions from the previous t-1 iterations plus the output of the t-th tree $f_t(x_i)$:

$$\widehat{M_\iota}^t = \widehat{M_{\iota-1}}^t + f_t(x_i) \tag{15}$$

The objective function of XGBoost consists of a loss function and a regularization term:

$$Obj^t = \sum_{i=1}^{n} L\left(M_i, \overline{M_i}^t\right) + \sum_{k=1}^{t} \Omega(f_k) \tag{16}$$

Among these, $L\left(M_i, \overline{M_i}^t\right)$is the loss function, commonly computed using mean squared error as shown in (3-7), while $\Omega(f_k)$is the regularization term for the kth tree:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j{}^2 \tag{17}$$

Tdenotes the number of leaf nodes in the tree, $w_j$represents the weight of the jth leaf node, and λ and γ are regularization parameters that control the number of leaf nodes and the sum of squares of leaf weights, respectively.

To efficiently optimize the objective function, perform a second-order Taylor expansion of (3-11):

$$Obj^t \approx \sum_{i=1}^{n} \left\{ g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right\} + \Omega(f_t)$$

$$g_i = \frac{\partial L\left(M_i, \overline{M_i}^{t-1}\right)}{\partial \left(\overline{M_i}^{t-1}\right)^2} \tag{18}$$

Furthermore, by selecting the optimal splitting point through a greedy algorithm, the gain calculation formula for splitting is:

$$Gain = \frac{1}{2}\left(\frac{(\sum g_L)^2}{\sum h_L + \lambda} + \frac{(\sum g_R)^2}{\sum h_R + \lambda} - \frac{(\sum g_L + \sum g_R)^2}{\sum h_L + \sum h_R + \lambda}\right) - \varsigma \tag{19}$$

Here, g_L, h_Lrepresent the sum of first- and second-order derivatives for all samples in the left subtree; g_L, h_Lrepresent the sum of first- and second-order derivatives for all samples in the right subtree.

3.2.3 CatBoost's Feature Engineering Model

CatBoost enhances the handling of categorical features through ordered boosting encoding, reducing prediction bias. CatBoost is essentially a variant of gradient-boosted decision trees, where its output is the weighted sum of all decision trees' outputs:

$$\widehat{M} = \sum_{m=1}^{n} \mu_m f_m(x) \tag{20}$$

CatBoost employs an ordered boosting strategy to process categorical features. To mitigate prediction errors, CatBoost uses a Bayesian smoothing formula to encode categorical features as time-ordered target encodings:

$$(x_i) = \frac{\sum_{jHistorical\ Samples, x_j = x_i} M_j + \tau\psi}{\sum_{j \in Historical\ Samples, x_j = x_i} 1 + \tau} \tag{21}$$

The numerator is the product of the prior mean of the target values for the same category across historical samples and the smoothing coefficient, while the denominator is the sum of the number of samples with the same category value across historical samples and the smoothing coefficient. Equation (3-15) enables ordered classification enhancement.

3.2.4 LightGBM: An Efficient Gradient Boosting Tree Model Improvement

To enhance computational efficiency, we integrated an improved model based on LightGBM. This model accelerates training speed and improves accuracy on large-scale datasets by leveraging histogram algorithms, one-sided gradient sampling, and mutually exclusive feature bundling metrics.

Unilateral gradient sampling is employed, retaining samples that significantly contribute to gradient ascent (high-gradient samples). The corrected gradient after sampling is as follows:

$$P^{'} = \sum_{i\in High\ Gradient} p_i + \frac{1-a}{b}\sum_{i\in Low\ Gradient} p_i \tag{22}$$

Here, a, b are used to determine the number of samples for high-gradient sampling and low-gradient sampling, respectively. $n_a = an, n_b = bn$.

High-dimensional sparse features, particularly encoded categorical features, are bundled through mutually exclusive feature bundling to reduce dimensionality. In sparse features, most values are zero, with only a few non-zero values.

$$conflict(x_i, x_j) = \frac{Non-Zero\ overlapping\ numbers}{min\left(non-zero(x_i), non-zero(x_j)\right)} \tag{23}$$

3.2.5 Predicting Actual Payout Amounts Using Stacking of Ensemble Learning

In our research, we use stacking, a form of ensemble learning, to integrate three base learner models.

The meta-features generated by the first-level model are as follows:

$$Mf = \left\{\widehat{M}_{1,test}, \widehat{M}_{2,test}, \widehat{M}_{3,test}\right\}^T \tag{24}$$

In this study, a simple mean-based learning algorithm was used to predict the final results:

$$\widehat{M}_{stacking} = \frac{1}{4}\sum_{i=1}^{4}\widehat{M}_{i,test} \tag{25}$$

To ensure data privacy and generate reliable meta-features, we use five-fold cross-validation to divide the training set into five mutually exclusive subsets. In each iteration, we train the base model using four subsets and use the remaining one as the “validation set” for prediction.

4. Model Formulation and Solution

4.1 Feature Selection

SMOTE resampling synthesizes samples from the minority class through interpolation; it is an oversampling method used to address class imbalance.

For a minority-class sample x_i, we find k nearest neighbors in its feature space using the Euclidean distance metric:

$$Dist(x_i, x_j) = \sqrt{\sum_{k=1}^{d}\left(x_{ik} - x_{jk}\right)^2} \tag{26}$$

Once the k nearest neighbors have been identified, the new sample is synthesized using the following formula:

$$x_{new,n} = x_{in} + r\left(x_{jn} - x_{in}\right)n = 1,2,\cdots d \tag{27}$$

Here, r is a random number between $(0,\ 1)$ used to control the position of the interpolation.

Through this process, SMOTE effectively increases the number of samples from minority classes, enabling the model to learn the features of these classes more fairly during training and thereby improving prediction performance for minority classes. We then perform feature selection in the same manner as in Section 6.1, using Pearson’s correlation coefficient for continuous features and ANOVA for categorical features.

4.2 Model Development and Analysis of Results

4.2.1 Building the CatBoost Classification Model

First, to address the challenge of handling categorical features, CatBoost encodes these features and combines this with random shuffling to prevent data leakage. First, the training samples are randomly shuffled:

$$X = \{x(1), x(2), \cdots x(n)\} \tag{28}$$

For the i-th sample in the sequence, the encoded value of its category feature c is calculated using the first i-1 samples:

$$Enc_{xi}(c) = \frac{S_{xi}(c)+\alpha\mu}{N_{xi}(c)+\alpha} \tag{29}$$

The definitions of $S_{xi}(c), N_{xi}(c)$ are as follows:

$$S_{xi}(c) = \sum_{j=1}^{i-1} I\left(c\left(x_j\right)\right)$$

$$N_{xi}(c) = \sum_{j=1}^{i-1} I\left(\left(x_i\right)\right) \tag{30}$$

These represent, respectively, the sum of the labels of samples in the previous i-1 samples that belong to the same class c as the current sample, and the number of samples in the previous i-1 samples that belong to the same class as the current sample.

The final prediction is the sum of the outputs from multiple decision trees, converted into probabilities via a sigmoid function:

$$\hat{p}(x) = \sigma\left(F_M(x)\right), F_M(x) = \sum_{i=1}^{M} f_m(x) \tag{31}$$

Here, $f_m(x)$ is the ensemble output of the mth decision tree, and $\sigma(z) = \frac{1}{1+e^{-z}}$ is the sigmoid function, which maps the result to the probability interval (0, 1). For a three-class classification task, the score function predicting membership in the three classes is: $\hat{p}(x) = \{p_1(x), p_2(x), p_3(x)\}$, and the class with the highest probability is selected as the final class.

During the iterative process, for a three-class classification task, the loss function for the entire training set is defined in terms of cross-entropy:

$$L = -\frac{1}{n}\sum_{i=1}^{n}\sum_{k=1}^{3} x_{ik}\, log(p_{ik}(x)) \tag{32}$$

Here, $x_{ik}$is the true label of class k for sample i, and the inner summation represents the sum of cross-entropies for individual samples.

During iterative training, the pseudo-residual is calculated using the negative gradient of the model's output$F_{m-1}$from the m iteration, and this serves as the fitting objective for the current tree. For a three-class classification task, each sample generates three pseudo-residuals, expressed as:

$$r_{ikm} = y_{ik} - {p_{ik}}^{m-1}(x) \tag{33}$$

Iterate through steps (4–9) to gradually reduce the multi-class cross-entropy loss.

$$F_m = F_{m-1} + \eta_m f_m \tag{34}$$

4.2.2 SVM-based classification model

SVM is an effective binary classification model whose core principle is to maximize the margin while allowing a small number of misclassified samples through the use of a soft margin. For the three-class problem in Question 2, train three classifiers with K = 3. Let the dataset $D = \{(x_1, y_1), \cdots, (x_N, y_N)\}$, where $x_i \in R^d, y_i \in \{1,2,3\}$.

Taking the kth classifier as an example, its optimization objective and constraints are:

$$\min_{w_k,b_k,\xi_{k,i}} \frac{1}{2}\|w_k\|^2 + C\sum_{i=1}^{N}\xi_{k,i}$$

$$s.t.\begin{cases} y_{k,i}(w_k\phi(x_i)+b_k) \geq 1-\xi_{k,i} \\ \xi_{k,i} \geq 0, \forall i = 1,2,\cdots,N \end{cases} \tag{35}$$

Here, $y_{k,i}$ is the label of the i-th sample in the k-th classifier.

By introducing a kernel function and a Lagrangian function, we transform this into a dual problem:

$$\frac{max}{a_{k,i}\sum_{i=1}^{N} a_{k,i}\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} a_{k,i}a_{k,j}y_{k,i}y_{k,j}K(x_i,x_j)}$$

$$s.t.\sum_{i=1}^{N} a_{k,i}y_{k,i} = 0 \tag{36}$$

The decision function for the kth classifier is:

$$score_k(x) = \sum_{i\in S_k} a_{k,i}y_{k,i}K(x_i,x) + b_k \tag{37}$$

The final classification result is the category corresponding to the classifier with the highest score:

$$\hat{y} = \underset{k=1,2,3}{argmaxscore_k}(x) \tag{38}$$

4.2.3 F1 Score Evaluation Metrics

The F1 score is the harmonic mean of precision and recall, used to comprehensively evaluate the performance of classification models, and is particularly suitable for situations involving class imbalance. For this study, it provides accurate evaluation results for imbalanced datasets where the proportion of severely overrepresented classes is less than 3% and the proportion of valid claims is no less than 85%.

$$Re\,c\,all = \frac{TP}{TP+FN} \tag{39}$$

The precision is the proportion of samples correctly classified as positive by the model out of all samples predicted as positive, reflecting the accuracy of positive class predictions:

$$Pr\,e\,cision = \frac{TP}{TP+FP} \tag{40}$$

Here, TP represents the number of samples that are actually positive and were correctly predicted as positive by the model. FP represents the number of samples that are actually negative but were incorrectly predicted as positive by the model. The F1 score is calculated using the following formula:

$$F1 = \frac{2\times Pr\,ecision\times Re\,call}{Pr\,ecision+Re\,call} \tag{41}$$

4.3 Analysis of Experimental Results

The following presents the results of the feature analysis, divided into the results of the importance analysis for categorical features and the results of the importance analysis for continuous features.After processing with the three models, the F1 scores on the training and test sets are as follows:As can be seen, the MLP model achieved the highest F1 score and performed the best.

Table 1: Model cross-validation results

Model	Weighted F1 score	Accuracy	Training set F1
CatBoost	0.7699±0.0028	0.8531	0.8605
MLP	0.9098±0.0046	0.9555	0.9568
SVM	0.6494±0.0050	0.8418	0.8418

Ultimately, we selected an MLP model, which is better suited for fitting nonlinear relationships, to make predictions on the test set. The results are as follows:

Table 2: MLP prediction results

Risk Level	Number of prediction samples	percentage
Low risk (Category 1)	2269	81.27%
Moderate risk (Category 2)	429	15.37%

High risk (Category 3)	94	3.94%

These results are similar to the distribution of the training set, indicating that the model has good generalization performance. However, there is a risk of cumulative error across two steps, which may affect the accuracy of risk assessment. This method involves two steps: predicting M and calculating the risk level. If the Stacking model's prediction of M values for certain claims is inaccurate, this error will be directly carried over to the risk level assessment, leading to amplified errors.

5. Conclusions

This research addresses the claims disputes and payment risks brought by the rapid development of the express logistics industry, constructing a comprehensive solution framework for claims risk segmentation, payout prediction, and risk classification. The proposed models effectively realize intelligent and automated claims settlement, providing technical support for enterprises to reduce costs and improve efficiency.

The risk labeling model based on quantile distribution and monotonicity constraints achieves reasonable risk classification, meeting distribution constraints and providing high-quality labels for subsequent modeling. The Stacking ensemble model, combined with feature engineering and outlier handling, optimizes actual payout prediction performance. The MLP-based risk classification model, using SMOTE to solve class imbalance, outperforms other classifiers with high weighted F1-Score and accuracy, accurately distinguishing risk levels. Overall, the research forms a complete technical system for logistics claims management, laying a solid foundation for intelligent claims settlement practice.

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Conflicts of Interest

The authors declare no conflict of interest.

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