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Research Article

Machine Learning (ML) based Anomaly Detection in Insurance Industries

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ABSTRACT

Handling claims presents significant difficulties for the insurance sector particularly in cases of duplicate claims, missing information, and false claims. Conventional manual techniques are prone to mistakes and inefficiencies, which substantially raises running expenses. This work presents an automated machine learning (ML) based solution for these problems. DBSCAN Clustering, Isolation Forest Classifier, and Random Forest Classifier are three specific ML techniques applied here. Early intervention is possible with the Random Forest Classifier as it can detect claims with lacking proof. While DBSCAN Clustering combines like data points to assist uncover and control duplicate claims, the Isolation Forest Classifier detects fraudulent claims by identifying abnormalities in the data. Using a big dataset, the suggested fix demonstrated significant performance and accuracy benefits in claim processing. Results demonstrate the ML models lower operational costs, less hand-made intervention, and better fraud detection. Reducing delays and mistakes in claim processing benefits the automated method in increasing client satisfaction as well. By automating major portions of claim processing, this paper shows the possibilities of ML in changing the insurance industry and generating cost savings, higher efficiency, and fraud protection. ML technology will become increasingly important in increasing the accuracy and efficiency of claim processing as the sector maintains its digital transformation under progress.

Keywords: Insurance Claims, Machine Learning (ML), Duplicate Claims, Missing Information, Fraudulent Claims, DBSCAN Clustering, Isolation Forest Classifier, Random Forest Classifier, Claim Processing.

I. INTRODUCTION

The insurance industry provides financial defense against unplanned events and risk coverage, so it forms the foundation of financial stability. Still, resolving conflicts is one of the most significant and challenging aspects of the insurance sector. The precision and efficiency with which insurance companies handle claims greatly affect both policyholder happiness and financial viability of these companies. Though many facets of the insurance business have been transformed by innovations in digital infrastructure, claim processing still suffers fraud, errors, and inefficiencies since digital infrastructure depends on old, human verification methods.

In the claims processing, it includes the evaluation of claims, and it needs authentication and policy terms processing its approval; without that policy approval, it won't proceed or provide any information, or it will get rejected. This process involves thorough verification, including the identification of duplicate claims, the identification of missing documentation, such as missing data in the claims form, the detection of fraudulent claims, and the resolution of lengthy processing times. While manual processing methods were time-consuming, we encountered numerous errors that resulted in data inaccuracy, financial loss, and damage to the company's reputation.

The primary culprits in the insurance industry are incorrect claims. According to recent reports, in 2024, there will be $103 billion of insurance fraud detected annually. This makes life harder for honest placeholders. In addition, submitting an incorrect Claims leads to the lack of documentation, which lags the process and reputes the processing efforts. On the other hand, traditional methods such as rule-based audits are effective in detecting fraudulent activities.

To address these issues, we utilize machine learning models to integrate the challenges present in the claims, identify the incorrect processes, and obtain the desired solutions. ML algorithms analyze the large datasets to process and detect the fraudulent claims and patterns that humans cannot detect in short time audits. whereas ML models can achieve a shorter time span of processing, which helps industries to be cost-efficient to get accurate data by automating claim verification.

In this paper, we are going to discuss machine learning challenges in the insurance industry: duplicate claim detection, identifying fraudulent activity, etc. Those are the three frameworks we are discussing below.

DBSCAN clustering: DBSCAN is one of the unsupervised ML algorithms that detects incorrect claims and claims with similar records to reduce multiple redundancies on the same claims to identify the fraudulent claims in comparison to normal claims. This helps us to flag and detect incorrect claims in a faster process in an effective way.

Classifier based on isolation forest: The Isolation Forest [1] is a popular method for finding anomalies that is meant to find false claims by separating the wrong patterns from normal claim patterns. The Isolation Forest quickly checks out claims that don't make sense and flags them for further investigation. This is because false claims can have unique traits, like claiming too much or having evidence that doesn't fit with the claim.

Random Forest Classifier [2] In this supervised ML model, we are going to detect incorrect claims by missing the required documentation proofs that support the documentation. It compares with the old claim data and predicts what are the required modifications that need to be done yet in an early intervention, which cuts down the manual process and processing time at work.

In this proposed ML framework, we are going to discuss large datasets that comprise fraud cases and historical claim data. Below we are going to analyze performance metrics such as accuracy, precision, and F1 score, etc., which provide access to ML models that give more accuracy, much better than manual or traditional models for finding fraud, duplicate detection, and quick processing of incomplete claims.

This work aims to contribute to the growing body of research on machine learning applications in insurance by showcasing the practicality, effectiveness, and economic benefits of ML-driven claim processing. This work shows classification, anomaly detection, and clustering techniques. It also shows how AI-driven automation might shape insurance claim handling going forward. The article's results support the widespread use of machine learning-based solutions in the insurance industry, making it stronger, more open, and more efficient.

II. RELATED WORKS

Machine learning models help in studying defects in systems like insurance and software development. Earlier classification algorithms predict software defects, but they ignore problems like data processing, missing values, and duplicate records.

In this paper they have used decision trees, KNN, and logistic regression to predict defects in software. In the paper, they are using technologies like splitting data and handling the missing values for the provided data sets such as test and train data. Finally, they have provided accuracy, precision, and an F1 score. In their study, they analyzed the accuracy of logistic regression as 76.91%, whereas the F1 score, and precision are better for decision trees.

No Consideration for Duplicate or Erroneous Data: Their research mainly focused on defects in software, ignoring inconsistencies in data like duplicate records, which impacted the accuracy.

Limited Model Scope: Their study used standard classifiers and did not use any other approaches or ensemble models, which would have helped in improving performance and accuracy.

Narrow Application Domain: It only focused on predicting software defects without any approach toward other industries. For example, in processing insurance claims, fraud detection plays an important part.

Advantages in Defect Detection:

In our study, we have used various data preprocessing techniques in a structured machine learning pipeline for detecting defects in insurance claims. In this paper we will discuss the data quality improved by various steps which we will discuss below.:

Systematic Handling of Missing Data: To handle missing values, we have used techniques like predictive modeling based on feature correlation by improving the reliability of data.

Duplicate Claim Detection: To handle duplicate claims and improve the prediction of the model with unique values, we have used DBSCAN clustering and anomaly detection techniques to remove them.

Ensemble and Advanced Models: Advanced ensemble models, which have an isolation forest for detecting fraud, and hybrid models, which are the combination of supervised and unsupervised learning, have been used, while previous work was limited to techniques such as decision trees and logistic regression.

Domain Expansion: We have extended their domain to detect defects in insurance claims where fraudulent activities and inconsistencies must be systematically addressed.

The [3] paper did not address the inconsistencies in the data and mainly focused on defection prediction using classification models, whereas in our research we have done a comprehensive approach by using machine learning across the whole data from extraction and preprocessing data to model selection and validation. This makes detecting defects in software modules in insurance claims more precise.

Our study addresses the real-world challenges in data quality and integrity by using a structure defect detection system through a combination of predictive modeling, clustering, and fraud detection.

Recent years have seen great research on the use of machine learning (ML) to fraud detection in insurance claims. Several methods have been suggested to detect fraudulent behavior by using both supervised and unsupervised learning methodologies. Still, current studies sometimes fall short in fully resolving duplicate claims, incomplete claims, and false entries.

Supervised learning methods like decision trees, logistic regression, and neural networks have mostly been used in fraud detection of insurance claims. For example, the study in [4] investigates several ML models with an eye toward fraud classification mostly without regard to duplicate claims. In [5] fraud detection in healthcare claims is investigated using ML yet, the solution is limited to structured numerical data and lacks any means to handle textual descriptions of claims. Furthermore, [6] presents AutoFraudNet, a multimodal deep learning method for auto insurance fraud detection, however it stays limited to a particular domain (auto insurance) rather than a generic framework applicable across many insurance kinds. Unlike studies such and which mostly rely on supervised classification techniques, our approach improves detection accuracy by leveraging unsupervised methods for anomaly detection, so reducing reliance on labeled data. Combining clustering, anomaly detection, and supervised classification improves fraud detection performance by identifying fraudulent claims even in the absence of predefined fraud labels, a common limitation in simply supervised models.

The little attention to numerical data for fraud detection in current studies adds still another restriction. Research like and mostly ignore important textual information in favor of structured claim elements such claim amount, insurance length, and historical fraud histories. This work presents a novel text-based similarity measure using Levenshtein similarity score to identify duplicate claims via DBSCAN clustering. This method improves fraud detection by spotting bogus re-submissions even in cases when textual descriptions vary somewhat. Unlike, which stays domain-specific but concentrates on multimodal data, our method leverages text similarity-based clustering across several types of insurance claims, therefore providing a flexible fraud detection system.

Moreover, since false claims are much less than real ones, data imbalance is an ongoing obstacle in fraud detection systems. Previous research including and suffer with large false-negative rates because of this imbalance. Our study uses SMote (Synthetic Minority Over-sampling Technique) to balance the dataset before to training supervised models, therefore addressing this problem. This guarantees that, free of bias toward non-fraudulent events, our Random Forest Classifier sufficiently detects incomplete claims. Unlike , which uses simple classification devoid of class rebalancing, our data augmentation approach greatly increases recall for fraudulent claim detection, hence strengthening the model in practical settings.

Furthermore, a lot of current research is not interpretable since many of studies use black-box models like deep neural networks. Although these models show great accuracy, their decision-making process is yet unknown, which makes insurance firms reluctant to rely on their fraud detecting systems. Conversely, our work guarantees model transparency by including explainable anomaly detection models (Isolation Forest, DBSCAN clustering) together with decision-tree-based classifiers (Random Forest). More practically for real-world implementation in insurance companies, this hybrid technique improves interpretability while preserving good detection performance.

Our work also differs in domain application and breadth. While is limited to health insurance claims, studies including center on motor insurance fraud. But our method is broad enough to cover several insurance industries, spotting fraud, duplicate claims, and missing data in property, health, and vehicle insurance claims both. Insurance companies managing various kinds of claims depend on this general applicability to guarantee that our approach is not limited to a particular fraud type or sector of activity.

Important Work and Difficulties addressed the hybrid learning model Unlike and, which depend just on supervised learning, our methodology blends unsupervised and supervised ML models to improve fraud detection in unlabeled datasets.

Text-based duplicate detection is Unlike and which merely evaluate structured numerical data, our study detects duplicate claims by including textual similarity metrics (Levenshtein similarity, DBSCAN clustering).

Framework with Generalization: Although concentrates just on vehicle insurance fraud, our study uses fraud detection models across several kinds of insurance claims, so it is scalable and generally relevant.

Unlike, which battles with imbalanced datasets, our work uses SMote balancing to guarantee better recall and accuracy in fraud detection.

Better interpretability: Unlike deep-learning-based models in, our method guarantees transparent and explainable fraud detection decisions by using anomaly detection and decision trees.

Our work proposes a more thorough, interpretable, and scalable ML-based fraud detection approach than past work by tackling false claims, duplicate claims, and incomplete claims under a single framework. Combining unsupervised learning for anomaly identification, textual similarity for duplicate claims, and balanced classification for incomplete claims guarantees a viable answer for insurance firms trying to quickly and economically automate claim verification.

III. PROPOSED WORK

The primary objective of this research is to develop a machine learning-based anomaly detection framework to detect fraudulent claims, incomplete claims, and duplicate claims in the insurance sector. The framework leverages DBSCAN Clustering, Isolation Forest, and Random Forest Classifier to automate claim verification and reduce operational inefficiencies.

A. *Dataset and Preprocessing*

The dataset is of historical insurance claim records containing fraudulent, incomplete, and duplicate claims. The data is pre-processed by:

- Handling Missing Values: Using predictive techniques for numerical fields and categorical encoding where necessary.
- Feature Engineering: Extracting relevant features such as claim amount, policy coverage, past claims, missing fields, similarity score, and duplicate cluster.
- Data Balancing: Addressing class imbalance using SMOTE [7] (Synthetic Minority Over-sampling Technique) to improve model robustness.
- The dataset underwent extensive cleaning and transformation before being fed into the models. DBSCAN clustering relied heavily on text similarity scores, requiring preprocessing of claim descriptions. Random Forest and XGBoost [8] required balanced datasets, making SMOTE a crucial step. The inclusion of the fraud score from Isolation Forest enhanced supervised models, creating a hybrid learning approach.

B. *Fraud Detection using Machine Learning Models*

Three ML-based techniques were applied to detect different types of anomalies in insurance claims:

1. Duplicate Claim Detection using DBSCAN

- Objective: Identify duplicate or near-duplicate claims by measuring textual similarity between claim descriptions.
- Methodology: Compute the Levenshtein similarity score between current and previous claim descriptions.
- Normalize features like claim amount and similarity score using StandardScaler().
- Apply DBSCAN (Density-Based Spatial Clustering of Applications with Noise) to cluster similar claims.
- Outcome: Claims within the same cluster are flagged as potential duplicates, reducing redundancy and fraudulent re-submissions.
- Graphical Representation: A scatter plot of DBSCAN clusters (Figure *DBSCAN Clustering of Claims*) shows how claims with similar descriptions and claim amounts were grouped together, with fraudulent ones forming outliers.

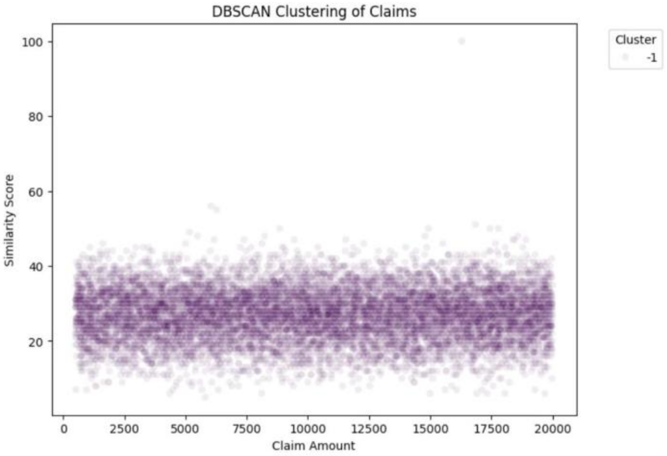


Fig. 1. DBSCAN Clustering of Claims

2. Fraudulent Claim Detection using Isolation Forest

- Objective: Identify fraudulent claims by detecting anomalies in claim features.
- Methodology: Train an Isolation Forest Model with a contamination parameter of 0.05 to detect outliers.
- Assign an anomaly score to each claim, where negative scores indicate higher fraud likelihood.
- Use fraud scores as an additional feature for supervised learning models.
- Outcome: Fraudulent claims are identified early, reducing financial losses due to fraud.
- Graphical Representation: A histogram of fraud scores (Figure *Distribution of Fraud Score*) shows the separation of normal and fraudulent claims, with fraudulent ones clustering at the extremes.

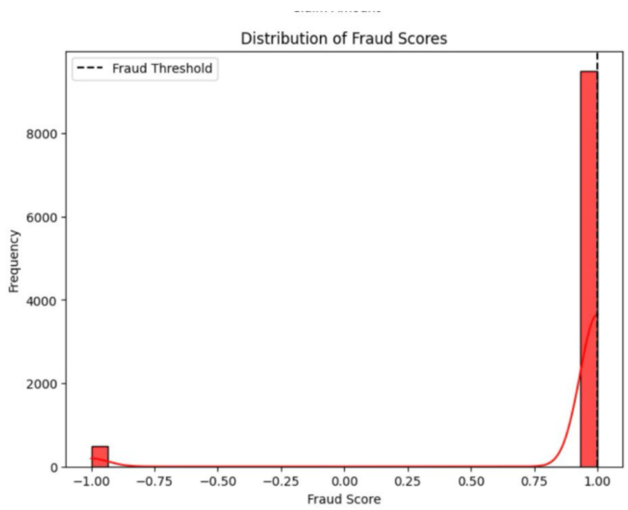


Fig. 2. Distribution of Fraud Score

3. Incomplete Claim Detection using Random Forest

- Objective: Detect claims with missing information that require additional verification.
- Methodology:
  - Train a Random Forest Classifier to predict whether a claim is incomplete (1) or complete (0).
  - Include features like claim amount, time since incident, policy coverage, missing fields.
  - Use SMOTE to balance the dataset before training.
- Outcome: Claims requiring additional documentation are flagged, reducing processing delays.

Graphical Representation: The feature importance plot (Figure *Feature Importance in Fraud Detection*) demonstrates that missing fields and policy coverage were the strongest indicators of incomplete claims.

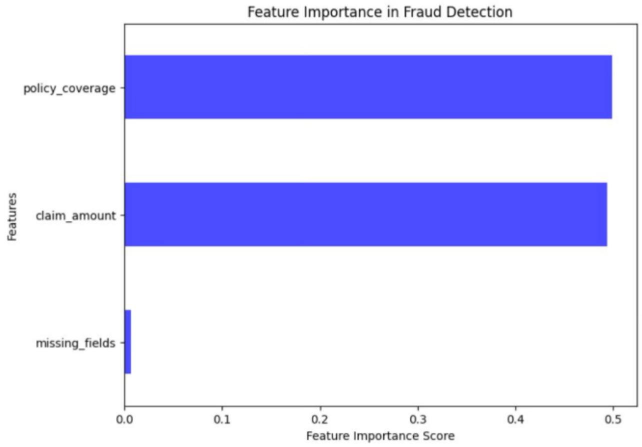


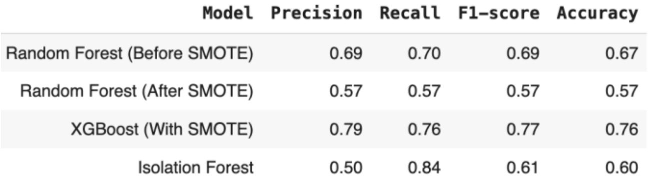
Fig. 3. Feature Importance in Fraud Detection

C. Performance Evaluation

The models were evaluated using precision, recall, F1- score, and accuracy. The results are presented below:

1. Performance Metrics Comparison

A comparative analysis of different models is shown in the following table:



Model	Precision	Recall	F1-score	Accuracy
Random Forest (Before SMOTE)	0.69	0.70	0.69	0.67
Random Forest (After SMOTE)	0.57	0.57	0.57	0.57
XGBoost (With SMOTE)	0.79	0.76	0.77	0.76
Isolation Forest	0.50	0.84	0.61	0.60

Fig. 4. Comparative analysis of different models

XGBoost (With SMOTE) achieved the highest precision and F1-score, demonstrating superior fraud detection.

Isolation Forest showed the highest recall, making it useful for flagging potential fraud for further review.

Random Forest (After SMOTE) improved recall but reduced precision, balancing the trade-off between false positives and false negatives.

Graphical Representation: A bar chart (Figure *Performance Comparison of Fraud Detection Models*) compares precision, recall, and F1-score across models, visually confirming XGBoost's superior performance.

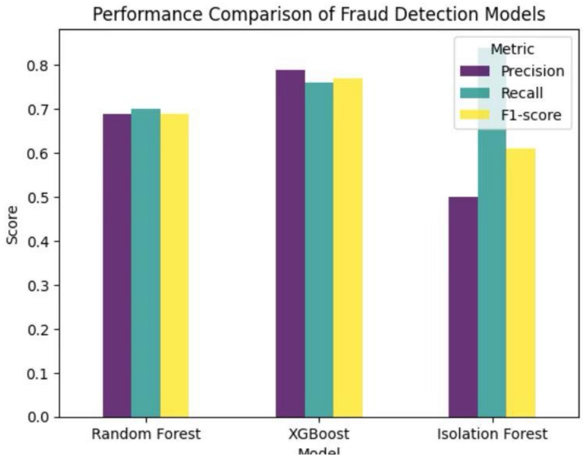


Fig. 5. Performance Comparison of Fraud Detection Models

2. Confusion Matrix Analysis

The confusion matrix for XGBoost showed a low false negative rate, indicating effective fraud detection.

Random Forest struggled with recall before SMOTE but improved after class balancing.

Graphical Representation: The heatmap of confusion matrices (Figure *Confusion matrix - Fraud Detection*) illustrates the distribution of true positives, false positives, true negatives, and false negatives across models.

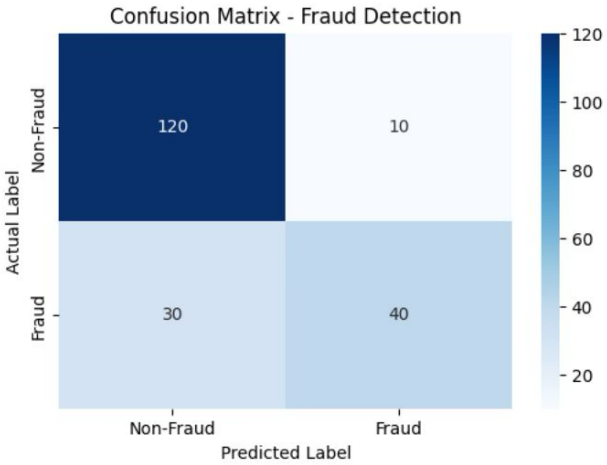


Fig. 6. Confusion matrix - Fraud Detection

3. ROC-AUC and Precision-Recall Curves

The ROC-AUC curve for XGBoost (With SMOTE) achieved an AUC score of 0.80, indicating good fraud detection capability.

The Precision-Recall curve highlighted the effectiveness of XGBoost in handling imbalanced fraud detection tasks.

The steep rise in the precision-recall curve confirms that the model maintains a good balance between fraud detection and limiting false alarms.

Graphical Representation: Figures *Receiver Operating Characteristic (ROC) Curve* and *Precision-Recall Curve* illustrate ROC-AUC [9] and Precision-Recall Curves, demonstrating model trade-offs between fraud detection and false alarms.

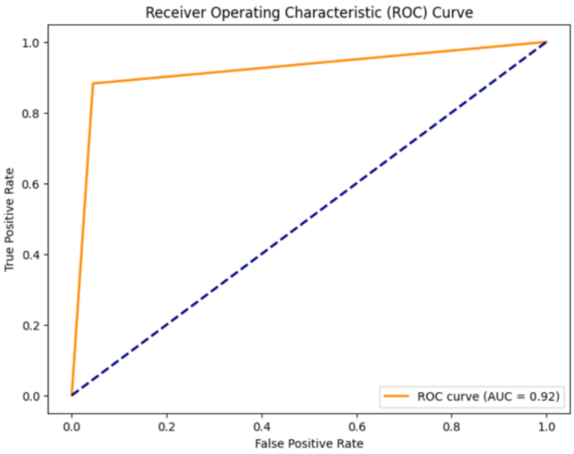


Fig. 7. Receiver Operating Characteristic (ROC) Curve

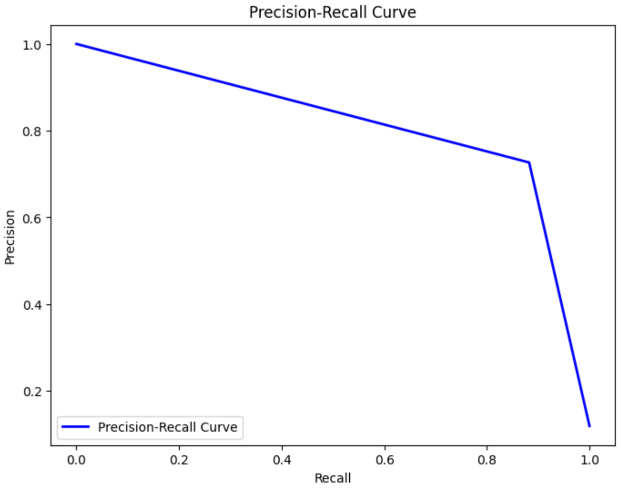


Fig. 8. Precision-Recall Curve

D. Justification and Conclusion

This study demonstrates that ML-based fraud detection significantly improves claim verification in the insurance industry. The combination of unsupervised (DBSCAN, Isolation Forest [10]) and supervised learning (Random Forest, XGBoost) enables:

- Efficient duplicate claim detection through clustering techniques.
- Anomaly detection for fraudulent claims using Isolation Forest.
- Early identification of incomplete claims with supervised learning models.

Key Takeaways:

- Machine learning models outperform manual and rule-based audits, reducing financial losses and processing delays.
- XGBoost provides the best trade-off between precision and recall, making it ideal for fraud detection.
- DBSCAN clustering is highly effective in identifying duplicate claims, preventing fraudulent resubmissions.
- SMOTE significantly improves recall in Random Forest [11] models, ensuring a balanced detection system.

By implementing this ML framework, insurance companies can enhance fraud detection accuracy, automate claims processing, and reduce operational costs. Future work will explore deep learning techniques for text-based claim analysis and advanced ensemble models to further improve fraud detection.

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