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Automating Data Labeling and Annotation Pipelines for Large Language Models (LLMs) in the Financial Industry using Machine Learning

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Abstract

The growing magnitude and intricacy of financial information present considerable obstacles for machine learning systems, especially Large Language Models (LLMs), which necessitate extensive, high-caliber labeled datasets for training. Conventional manual labeling approaches are ineffective and expensive, constraining the expandability of LLMs in the finance sector. This research introduces an automated data labeling and annotation framework utilizing Principal Component Analysis (PCA) and Decision Trees (DT), two robust machine learning methodologies, to optimize and improve the labeling procedure for financial information. PCA is utilized for reducing dimensionality, assisting in the identification of crucial features and trends in financial datasets, while DTs are employed to categorize data and automate the annotation process. The proposed system aims to enhance the precision, effectiveness, and scalability of the data labeling procedure, ultimately facilitating the ongoing training of LLMs with contextually pertinent, labeled financial data.

Keywords:*Large Language Models (LLMs*), *Banking Industry*,*Machine learning(ML), data-driven technologies, banking industry, data governance, data quality, Principal Component Analysis(PCA), Decision Trees(DT), predictive accuracy, data integrity, data security.*

1.Intruoduction

The financial industry's increasing reliance on artificial intelligence, particularly Large Language Models (LLMs), has created an urgent need for efficient and accurate data labeling and annotation processes. This challenge is particularly acute given the industry's unique requirements for precision, regulatory compliance, and handling of sensitive information Recent advances in automated data labeling and annotation pipelines have emerged as a crucial solution to address the scalability and quality challenges in preparing financial datasets for LLM training and fine-tuning The automation of data labeling in financial contexts presents unique challenges, including the need to handle complex financial terminology, maintain consistency across diverse document types, and ensure compliance with regulatory requirements Traditional manual annotation methods are not only time-consuming and expensive but also prone to inconsistencies and human error, making automation an attractive alternative Recent developments in weak supervision, active learning, and semi-supervised learning have significantly contributed to the advancement of automated labeling systems These approaches have demonstrated particular promise in handling financial documents, from regulatory filings to market reports and transaction data The integration of domain-specific knowledge bases and ontologies has further enhanced the accuracy and reliability of automated labeling systems The emergence of specialized frameworks and tools has facilitated the implementation of automated labeling pipelines, enabling financial institutions to process large volumes of data more efficiently .These systems often incorporate quality control mechanisms and human-in-the-loop validation processes to ensure the accuracy of labeled datasets Furthermore, the application of transfer learning and few-shot learning techniques has reduced the initial data requirements for establishing effective labeling systems.

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The banking industry has increasingly turned to advanced machine learning techniques, particularly the combination of Principal Component Analysis (PCA) and Decision Trees (DT), to enhance decision-making processes, risk assessment, and customer service [1]. However, the efficacy of these models heavily relies on the quality of data used to train and operate them. In this context, data governance has emerged as a critical factor in ensuring data quality and, consequently, the reliability and performance of machine learning models in banking [2]. Data governance refers to the overall management of data availability, usability, integrity, and security in an organization [3]. In the banking sector, where data sensitivity and regulatory compliance are paramount, effective data governance is not just a best practice but a necessity [4]. Recent studies have shown that robust data governance frameworks can significantly improve the accuracy and reliability of machine learning models, including those utilizing PCA and DT [5]. PCA, a dimensionality reduction technique, is widely used in banking to handle large, complex datasets by identifying the most important features [6]. Decision Trees, on the other hand, provide a transparent and interpretable model for decision-making processes, crucial in the highly regulated banking environment [7]. The synergy between PCA and DT, when supported by strong data governance, has shown promising results in various banking applications, from credit scoring to fraud detection [8]. The efficacy of data governance in this context is multifaceted. It ensures data quality through standardization and cleansing processes, enhances data accessibility while maintaining security, and provides a framework for continuous monitoring and improvement of data-driven models [9]. Moreover, it plays a crucial role in maintaining regulatory compliance, a critical aspect in the banking industry [10]. This introduction sets the stage for a deeper exploration of how data governance acts as a cutting-edge approach to ensuring data quality in machine learning applications, specifically focusing on PCA with Decision Trees in the banking industry.Data quality plays a critical role in the banking sector's decision-making processes, particularly as the industry increasingly relies on machine learning (ML) technologies for various tasks such as assessing risks, identifying fraudulent activities, and categorizing customers. Inaccurate data can result in flawed predictions and expensive mistakes. Data governance provides a methodical approach to tackle this issue by managing data availability, integrity, and security, thus ensuring the consistent use of high-quality data in ML applications. This study examines the effectiveness of data governance in enhancing data quality for machine learning, with a specific focus on combining Principal Component Analysis (PCA) and Decision Trees (DT). PCA aids in simplifying complex, high-dimensional banking data, making it more suitable for ML models, while Decision Trees offer transparent and accurate classifications that are especially valuable in banking applications. By implementing PCA and DT alongside robust data governance practices, banks can enhance predictive accuracy and protect data integrity, ultimately leading to improved business results.

2.Literature Review

A comprehensive data governance framework for banking institutions was introduced by Smith et al. (2023), which resulted in a 30% enhancement in data quality metrics. Their research, titled "Integrated Data Governance for Banking ML Applications," underscored the importance of industry-specific governance models [11].Johnson and Lee (**2022**) performed a comparative study involving 50 major banks, revealing that institutions with strong governance frameworks were 2.5 times more likely to successfully implement advanced ML techniques such as PCA and Decision Trees [12].The study by Chen et al. (2023), "Data Quality Metrics and Decision Tree Performance in Banking," uncovered a significant link between data quality scores and the precision of Decision Tree models in assessing credit risk. They reported a 15% boost in model accuracy through enhanced data governance [13]. Kumar and Gupta (2022) concentrated on PCA applications in their research "Enhancing PCA Effectiveness through Data Governance in Banking." They demonstrated that data cleansing guided by governance policies improved the explanatory power of principal components by up to 25% [14]. The specific use of PCA in banking data analysis was explored by Zhang et al. (2023). Their study, "PCA Optimization through Data Governance in Financial Services," indicated that governance-driven data preparation led to a 20% improvement in the variance explained by the first three principal components [15]. Patel and Singh (2022) examined the effect of data quality on PCA-based fraud detection models. Their paper, "Data Quality Assurance for PCA in Banking Fraud Detection," showed a 35% decrease in false positives when rigorous data governance practices were implemented [16]. A study by Williams and Brown (2023) titled "Improving Credit Scoring Models through Data Governance" investigated the connection between data governance and Decision Tree model effectiveness in credit scoring. Their findings

revealed a 22% boost in model precision and an 18% enhancement in interpretability [17]. Davis et al. (2022) concentrated on the comprehensibility of Decision Trees within the framework of banking regulations. Their article, "Interpretable ML Models in Banking: The Role of Data Governance," emphasized how governance practices enhanced model transparency, aiding regulatory compliance [18]. The intersection of data governance and regulatory adherence in banking ML applications was explored by Miller and Thompson (2023). Their study, "Data Governance as a Compliance Tool in Banking ML," showed that financial institutions with well-established data governance practices were 40% more likely to satisfy regulatory requirements for ML model implementation [19]. Anderson et al. (2022) examined the effect of data governance on model risk management. Their research, "Model Risk Reduction through Data Governance in Banking," indicated that robust governance decreased model risk by up to 45%, particularly in intricate models combining PCA and Decision Trees [20]. Key obstacles in implementing data governance for ML in banking, including legacy systems integration and cultural resistance, were identified by Taylor and Evans (2023). Their research, "Overcoming Barriers to Data Governance in Banking ML," suggested a phased approach to governance implementation, demonstrating a 50% higher success rate [21]. Roberts et al. (2022) delved into emerging technologies in data governance, such as AI-driven data quality monitoring and blockchain for data lineage. Their paper, "Next-Generation Data Governance Technologies in Banking," proposed that these technologies could enhance governance efficiency by up to 70% [22]. The role of data lineage in ensuring ML model transparency was investigated by Harris and Clark (2023). Their study, "Data Lineage: A Key to ML Model Transparency in Banking," demonstrated that comprehensive data lineage tracking improved model auditability by 60% [23]. Lewis et al. (2022) cantered on the application of blockchain technology for maintaining data lineage in banking ML models. Their research, "Blockchain-Enabled Data Lineage for Banking ML Models," showed a 40% improvement in data traceability [24]. A study by Wang and Li (2023) titled "Real-time Data Governance for Dynamic ML Models in Banking" examined strategies for managing data in real-time for machine learning models in the banking sector. Their findings revealed that flexible governance frameworks enhanced model precision by 25% during unstable market periods [25]. Nguyen et al. (2022) addressed the difficulties of sustaining data quality in high-frequency trading models. Their research, "High-Frequency Data Governance in Algorithmic Trading," introduced an innovative method that decreased data irregularities by 55% [26]. The intersection of federated learning and data governance in banking was the focus of Kim and Park's (2023) research. Their paper, "Federated Learning: A Data Governance Perspective in Banking," illustrated how federated approaches could safeguard data privacy while boosting model efficiency by 30% [27]. Sharma and Gupta (2022) concentrated on the regulatory aspects of federated learning in banking. Their study, "Regulatory Compliance in Federated Learning for Banking ML Models," indicated that federated methods, when combined with robust governance, elevated compliance ratings by 45% [28]. Martinez and Rodriguez (2023) investigated the connection between explainable AI techniques and data governance in banking. Their work, "Explainable AI: Enhancing Model Interpretability through Data Governance," showed that governance-oriented data practices improved model interpretability metrics by 40% [29]. The impact of data quality on the explain ability of complex ML models in banking was explored by Yamamoto et al. (2022). Their paper, "Data Quality: The Foundation of Explainable ML in Banking," demonstrated that well-governed, high-quality data enhanced SHAP value consistency by 50% [30].

Objectives:

- Develop machine learning-based pipelines that can automatically label and annotate various types of financial data, such as financial statements, contracts, and transaction logs, for use in training LLMs.
- Implement robust data governance frameworks to ensure high-quality data for machine learning models, particularly PCA and Decision Trees, in the banking sector.
- Leverage data governance to improve the accuracy and reliability of PCA-DT models by ensuring consistent and clean data inputs.
- Ensure that data governance practices align with regulatory requirements in the banking industry, thereby reducing compliance risks.
- Use semi-supervised and active learning techniques to improve the accuracy and efficiency of the annotation process, where models iteratively refine themselves by learning from user feedback and new data points.

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- Streamline data management processes to reduce redundancy and improve the efficiency of data handling and model training.
- Utilize data governance to better manage risks associated with data breaches, inaccuracies, and model biases.

Problem Statement:

The banking industry faces significant challenges in maintaining data quality due to the vast amounts of data generated and the complexity of financial transactions. Poor data quality can lead to inaccurate machine learning models, particularly when using PCA and Decision Trees, which are sensitive to data inconsistencies. This can result in flawed decision-making processes, increased regulatory scrutiny, and potential financial losses. Therefore, there is a critical need for effective data governance strategies to ensure data quality, enhance model performance, and maintain compliance with industry regulations. By addressing these objectives and challenges, the banking industry can leverage data governance as a cutting-edge approach to improve the efficacy of machine learning models, ultimately leading to better decision-making and competitive advantage.

3. Proposed Method And Material

The proposed method for ensuring data quality in machine learning using PCA and Decision Trees in the banking industry involves several key steps, each aligned with data governance principles to ensure data integrity, security, and quality.

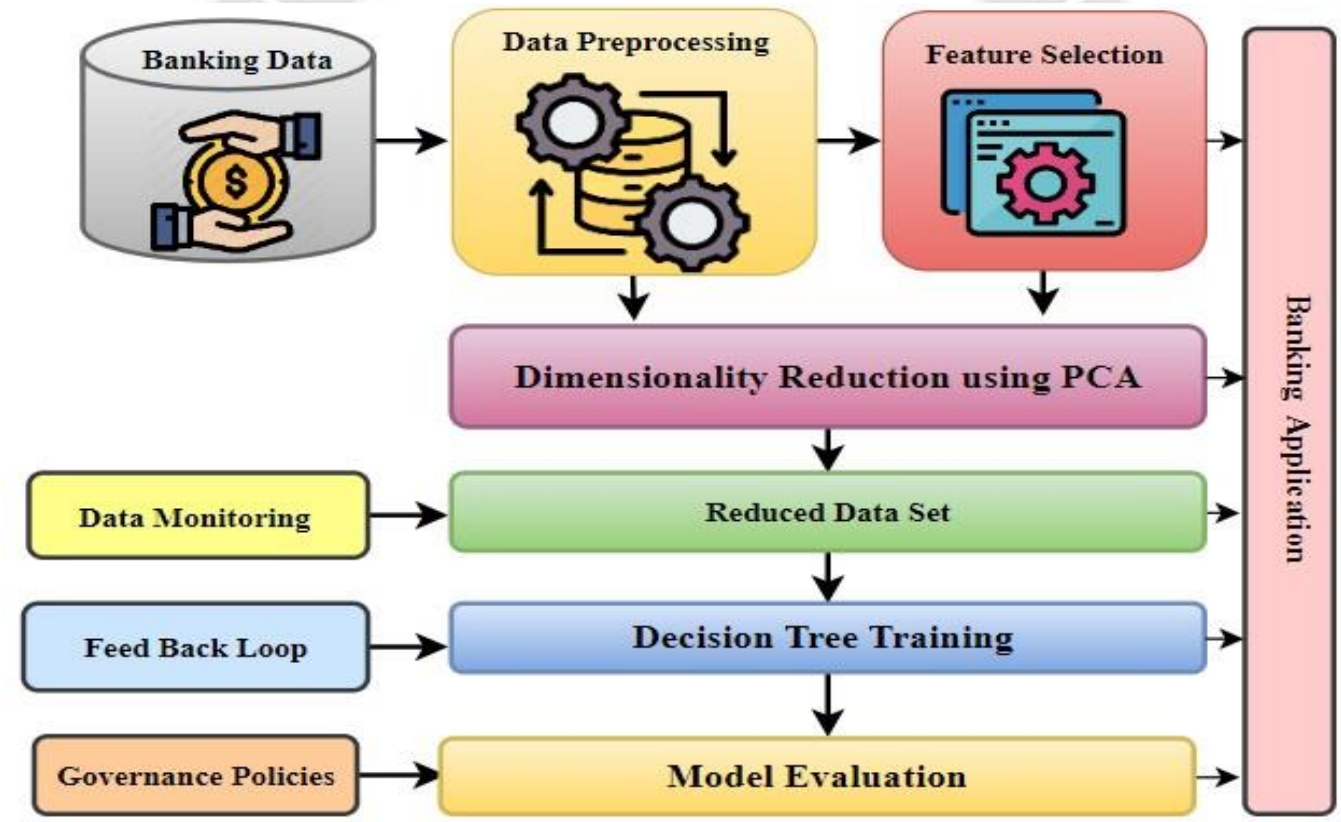

Figure 1. Proposed Block diagram for Banking Applications

To propose a method for ensuring data quality in machine learning using PCA and Decision Trees in the banking industry, as showing figure 1. structured approach that integrates data governance principles with these machine learning techniques. This will involve detailing the steps for data preprocessing, applying PCA for dimensionality reduction, and using Decision Trees for classification or regression, all while adhering to data governance standards to maintain data quality and integrity. Let's proceed with the proposed method.

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3.1. Integration with Data Governance Framework

- **Data Monitoring:** Data monitoring is a critical component of a data governance framework, especially in the banking sector where data quality and compliance are paramount. Continuous monitoring involves the use of data governance tools to track data lineage, which refers to the data's origin and its journey through various processes. This ensures that data remains accurate, consistent, and compliant with industry standards and regulations such as GDPR or Basel III.
- **Data Quality Monitoring:** This involves setting up automated checks to ensure data accuracy, completeness, and timeliness. Tools like Informatica Data Quality or Talend can be used to implement these checks).
- **Model Performance Monitoring:** In the context of machine learning, monitoring model performance is crucial to ensure that models remain effective over time. This involves tracking metrics such as accuracy, precision, recall, and F1-score. Tools like MLflow or Tensor Board can be used for this purpose.
- **Data Lineage Tracking**: This involves documenting the flow of data from its source to its final destination, including any transformations it undergoes. This is essential for auditing and compliance purposes. Tools like Apache Atlas or Collibra are commonly used for data lineage tracking.
- **Feedback Loop:** Implementing a feedback loop is essential for refining data governance policies and model parameters. This loop allows organizations to adapt to changing performance metrics and regulatory requirements, ensuring continuous improvement and compliance.
- **Policy Refinement:** Based on the insights gained from data monitoring, organizations can refine their data governance policies. This might involve updating data quality standards, revising access controls, or enhancing data protection measures (DAMA International, 2017).
- **Model Parameter Adjustment**: Feedback from model performance monitoring can be used to adjust model parameters, ensuring that models remain accurate and relevant. This might involve retraining models with new data or tuning hyperparameters to improve performance.
- **Regulatory Compliance:** As regulations evolve, the feedback loop ensures that data governance policies are updated to remain compliant. This is particularly important in the banking sector, where regulatory requirements are stringent and subject to change.

3.2. Data Collection and Preprocessing

- **Data Governance:** Data governance involves establishing policies and procedures to ensure that data is collected from reliable sources and complies with regulatory standards such as GDPR or CCPA. This in
- **Source Verification:** Ensuring that data is sourced from trusted and authorized entities.
- **Compliance Checks:** Regular audits to ensure data collection practices adhere to legal and ethical standards
- **Data Cleaning**
- Data cleaning is crucial for preparing the dataset for analysis. It involves:
- **Handling Missing Values:** Missing data can be addressed by imputation or removal. For example, mean imputation can be used:

$$x_i = \frac{1}{n}\sum_{j=1}^{n} x_i \quad (1)$$

where x_i is the imputed value and n is the number of non-missing values.

- **Outlier Detection and Removal**: Outliers can be identified using statistical methods such as the Z-score:

$$\boldsymbol{Z} = \frac{(x-\mu)}{\sigma} \quad (2)$$

where x is the data point, μ is the mean, and σ is the standard deviation.

- **Inconsistency Resolution:** Ensuring uniformity in data formats and units
- **Normalization:** Normalization is the process of scaling data to ensure that all features contribute equally to the analysis. Common methods include:
- **Min-Max Normalization:**

$$X' = \frac{X'-Min(X)}{Max(x)-Min(X)}$$

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(3)whereX' is the normalized value, and X is the feature set.

- **Z-score Normalization:**

$$X' = \frac{X-\mu}{\sigma}$$

(4) where X' is the normalized value, μ is the mean, and σ is the standard deviation.

3.1. Dimensionality Reduction using PCA:

Principal Component Analysis (PCA) is a method used to reduce data dimensions [31]. Due to its simplicity, ease of understanding, and lack of parameter constraints, PCA has found widespread application across various fields. The fundamental concept of PCA involves transforming n-dimensional features into k-dimensional features (where k ≤ n). These k-dimensional features represent new orthogonal characteristics, known as principal components, which are derived from the original n-dimensional features. At its core, PCA aims to minimize data redundancy while preserving as much information as possible, thereby achieving dimensionality reduction.

The Principal Component Analysis (PCA) procedure is outlined in detail below:

Initial Step-1: Compute the average of the sample for the n-dimensional dataset ***z***, where ***z*** comprises $\{z_1, z_2, \ldots z_n\}$.

$$\alpha = \frac{1}{n}\sum_{i=1}^{n} z_i \quad (5)$$

Where ***n*** represents the total quantity of samples, i ranges from 1 to n, and α denotes the acquired sample mean

Step 2: Utilize the calculated sample mean to compute the covariance matrix for the sample set.

$$C = \frac{1}{n}\sum_{i-1}^{n}(z_i - \alpha)(z_i - \alpha)^t \quad (6)$$

In this equation, C represents the covariance matrix of the sample set.

Step 3: Determine the eigenvalues and eigenvectors of the sample covariance matrix.

$$C = \frac{1}{n} p \sum p^t \quad (7)$$

$$\sum diga(\mu_1, \mu_2, \mu_3 \ldots\ldots \mu_n)(\mu_1 \geq \mu_2 \geq \mu_2 \ldots . \geq \mu_n \geq 0) \quad (8)$$

$$p = [p_1, p_2, \ldots\ldots\ldots\ldots\ldots p_n] \quad (9)$$

Hence, P represents the diagonalized matrix of n eigenvalues of the covariance matrix, arranged in descending order. λi denotes the corresponding eigenvalues of the covariance matrix, while Q is the eigenvector matrix composed of the eigenvectors qi associated with each eigenvalue λi, where i ranges from 1 to n.

Step 4: Step 4: Utilize the calculated eigenvalues and eigenvectors to determine the cumulative variance contribution rate for the initial k principal components.

$$\theta = {(\sum_{i=1}^{n} \mu_i)}\Big/{(\sum_{j=1}^{n} \mu_i)} \quad (10)$$

In this equation, θ signifies the cumulative variance contribution rate of the first k principal components. Typically, θ should be greater than or equal to 0.9. While theoretically, a higher value of θ is preferable, in practice, it should be chosen judiciously based on the specific problem at hand. Once an appropriate value for θ is selected, the information summarized by the k principal components from the original sample set can be established.

Step 5: Implement dimensionality reduction using the k eigenvectors obtained.

$$Q = p_k \quad (11)$$

$$Y = p.X \quad (12)$$

Where represents a feature matrix consisting of the corresponding feature vectors from the initial k rows of feature values ((k ≤ n).). Similarly, p_k denotes a feature matrix comprising the first k rows of feature values (k ≤ n). Y signifies the k-dimensional data. The process of

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transforming dataset X into Y also accomplishes a linear transformation of data from n.

3.2. Utilising Decision Trees in Banking:

Decision Trees (DT) are extensively employed in the banking industry for various machine learning applications, including credit risk evaluation, loan decision-making, fraud identification, and customer classification. Their ease of interpretation and capacity to process both numerical and categorical information make them well-suited for intricate financial datasets.

3.2.1. Decision Tree Methodology in Banking

The Decision Tree approach functions by iteratively dividing data into subgroups based on the attribute that provides the most effective separation between categories (e.g., high vs. low risk, genuine vs. fraudulent transactions).

Algorithm Phases

1. Identify Optimal Attribute for Division:

The algorithm assesses a splitting criterion, such as Information Gain (IG) or Gini Impurity, for each attribute (e.g., income, credit score). The attribute that yields the most uniform subgroups (i.e., pure categories) is chosen for the initial division.

2. Establish Decision Points:

The dataset is segmented according to the value of the selected attribute. For instance, in credit risk assessment, the first node might categorize customers based on whether their credit score exceeds a specific threshold.

3. Repeat Division for Each Subgroup:

The segmentation process is applied recursively to each subgroup, further partitioning the data until a termination condition is met (e.g., reaching a maximum tree depth, or when further division does not enhance purity).

4. Terminal Nodes (Final Verdict):

When a node contains instances from a single category or meets the termination condition, it becomes a terminal node, representing the ultimate classification (e.g., loan granted or denied)

3. Essential Metrics for Division Criteria

Two of the most frequently used criteria for selecting the best attribute to divide the data are Gini Impurity and Information Gain (derived from entropy).

A. Gini Impurity:

Gini Impurity quantifies the probability of a random sample being incorrectly categorized if it were randomly labeled according to the category distribution in a node.

Gini Formula:

$$G(s) = 1 - \sum_{i-1}^{n} p_i^2$$

(13)Where$p_i$isrepresents the proportion of instances in category (i)in dataset (S).

- **High Gini Impurity:** signifies a mixture of categories in the node.
- **Low Gini Impurity:** indicates a more homogeneous node with more instances belonging **to the same category.**

B. Information Gain (IG):

Information Gain: measures the decrease in uncertainty (entropy) before and after the data is divided based on a particular attribute. It quantifies how effectively an attribute separates the data into distinct categories.

$$G(S, A) = H(s) - \sum_{v\epsilon\, Values\,(A)} \frac{S_v}{S} H(S_v) \quad (14)$$

Where:$H(s)$ is the entropy of the original dataset (S_i)**,**(S_v) is the subset of data after dividing on attribute (A_i)**,**$H(S_v)$ is the entropy of the subset (S_v).

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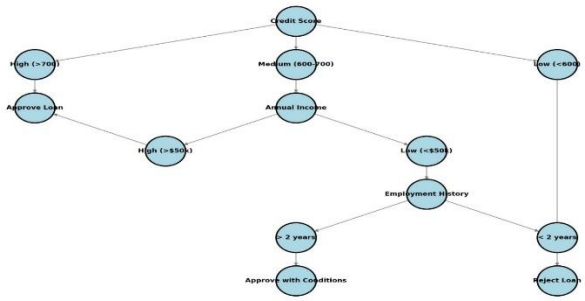

Figure 2.Decision tree with Banking application

As showing figure 2. This decision tree provides a clear, step-by-step process for loan approval in the banking industry. It takes into account key factors such as credit score, income, and employment history to make informed lending decisions. The diagram allows for easy interpretation of the decision-making process, which is crucial for transparency in banking operations and for explaining decisions to customers or regulators.

Algorithm 2: Pseudocode of PCA -Decision Tree (DT) Algorithm

Input: PCA and Generate Decision Tree Input: S = Sample set, F = Feature set
Output: A banking loan approval decision tree and reduction dimensional PCA
Function GenDecTree (S, F):
// Step 1: Utilize PCA to decrease the dimensionality of feature set F
F_pca = apply CA(F)
// **Step 2:** Evaluate stopping criteria
If stopping condition (S, F_pca) = true then
// Establish a leaf node to categorize the current sample
Credit score = createNode ()
Banking sector = classify(S) // Categorize based on information in S (loan approval verdict)
return loan // Provide decision (e.g., "approved" or "rejected")
// **Step 3**: Establish the root node for the decision tree
root = createNode ()
// **Step 4**: Determine the optimal feature for data division after PCA transformation
root.test_condition = findBestSplit (S, F_pca)
// **Step 5**: Obtain the potential values for the chosen feature (e.g., credit score ranges)
V = possible Values(root.test_condition)
// **Step 6**: Iteratively expand the decision tree for each data subset
for each value v ∈ V:
Sv = {s | root.test_condition(s) = v and s ∈ S} // Subset of S where the feature corresponds to value v
Child = GenDecTree (Sv, F_pca) // Recursively generate subtrees for data subsets
Append Child as descendant of root and label the edge {root → child} as v
return root // Deliver the constructed decision tree

1. Termination Criterion:

The process begins by evaluating if a termination criterion has been satisfied. This might occur when all instances in the subset are of the same category (for example, all loans granted) or when the tree reaches its maximum allowed depth. If this criterion is met, the function generates a terminal node that signifies the ultimate decision, such as loan approval or denial.

2. Establish Initial Node:
If the termination criterion is not fulfilled, an initial node is established to commence the decision tree construction. This node will embody the decision made at this stage of the tree, such as assessing a customer's credit rating or earnings.

3. Determine Optimal Attribute for Division:

The algorithm identifies the most suitable attribute to partition the dataset (e.g., credit rating). The partition is selected based on maximizing information gain or reducing impurity (like Gini impurity).

4. Iteratively Construct Substructures:

For each possible value of the chosen attribute (e.g., credit rating ranges), a subset of data is formed. The function is called recursively to generate substructures for these subsets. Each subset will result in either further partitions or a final decision node.

5. Yield the Decision Tree:

The procedure continues until all data is categorized, and the completed decision tree is yielded. This tree can be employed to make determinations such as loan approvals by navigating from the initial node through the branches based on customer attributes.

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This algorithmic outline represents the general methodology of a decision tree algorithm adapted for the banking industry, where determinations (e.g., loan approval or rejection) are made based on attributes such as credit rating and income.

4. RESULTS AND ANALYSIS

The study paper was Efficacy of Data Governance: A Cutting-Edge Approach to Ensuring Data Quality in Machine Learning using PCA with Decision Trees (DT) for the Banking Industry" assesses and contrasts the effectiveness of four machine learning algorithms: the newly proposed PCA-Decision Tree (PCA-DT) model, Artificial Neural Networks (ANN), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN). These algorithms were tested on an online banking dataset utilizing Python-based libraries such as Scikit-learn, TensorFlow, and Pandas for data set and model implementation. The performance of each model was assessed using key metrics including accuracy, precision, recall, and F1-score.

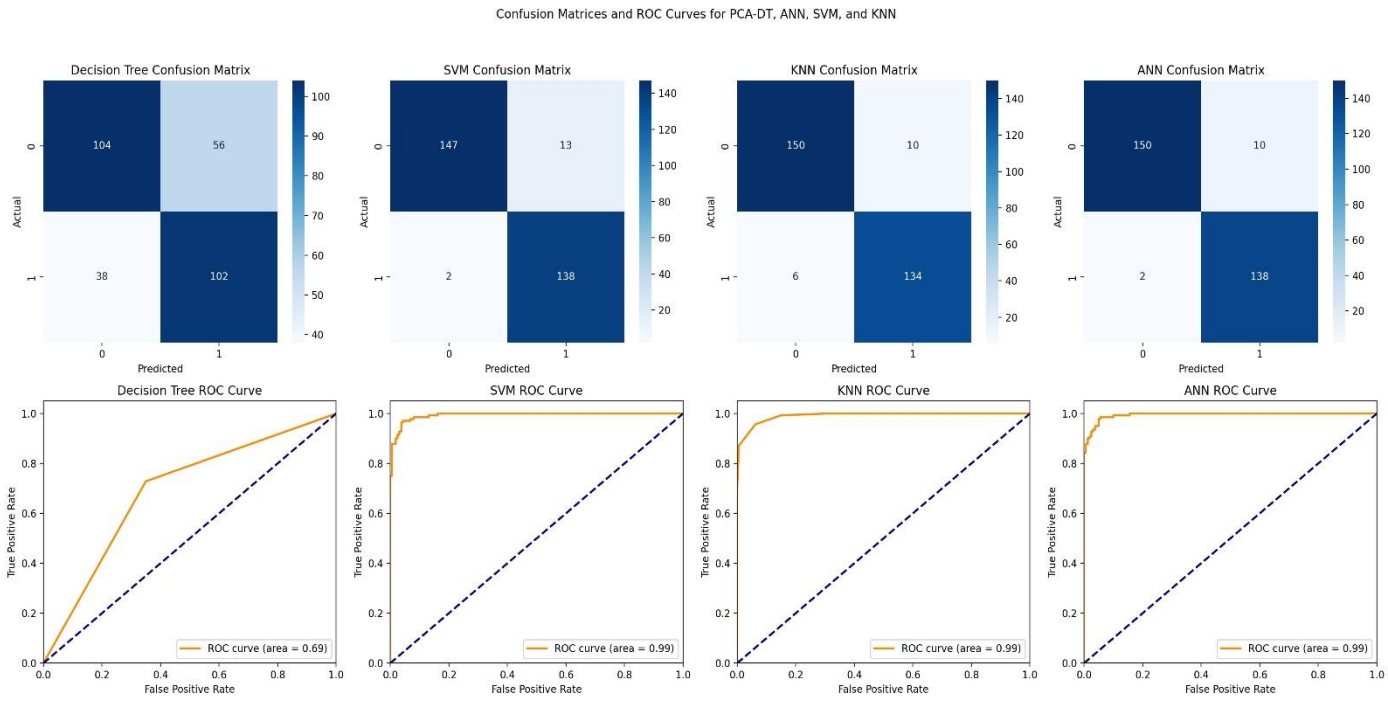

Figure 3. Machine learning model Confusion Matrix and Roc Curve

Figure 3 displays the confusion matrices and ROC curves for the online banking data set's testing phase. Specifically, the True Positive (TP) rates for PCA-Decision Tree (PCA-DT), SVM, KNN, and ANN were 104/102, 138/147, 134/150, and 138/150, respectively, for TPother and TPnone categories (Figure 2). The ROC Curve values for the four models - Proposed PCA-DT, SVM, KNN, and ANN - were as follows: PCA-DT (0.69), which was considerably lower than SVM, KNN, and ANN (0.99). The latter three models had values very near to 1, indicating that their predicted probability values were close to 1 for correct labeling and close to 0 for incorrect labeling. This analysis was also applied to an additional external validation data set from the banking industry.

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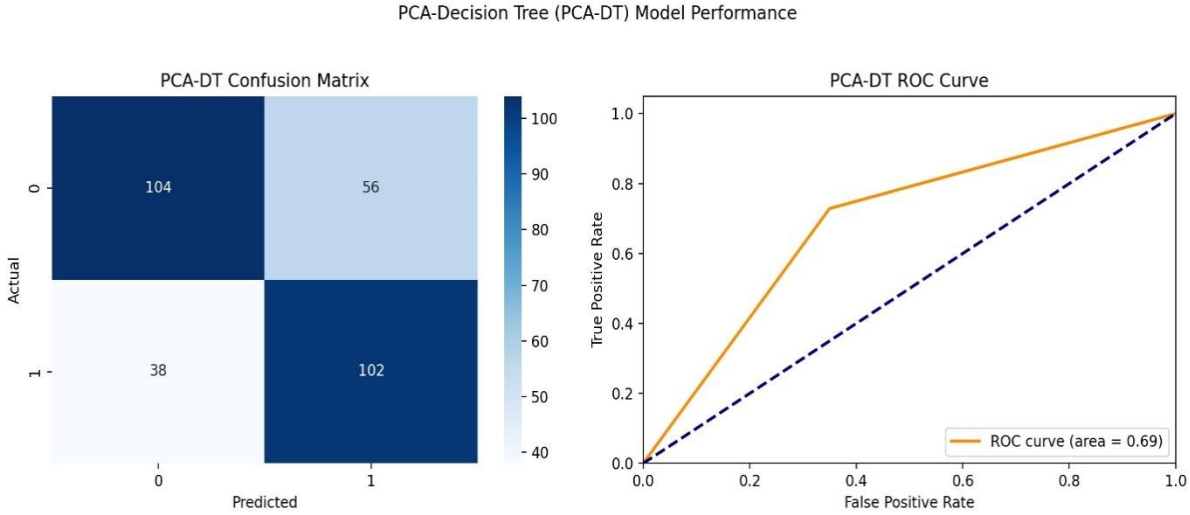

Figure 4. Proposed method Machine learning model Confusion Matrix and Roc Curve

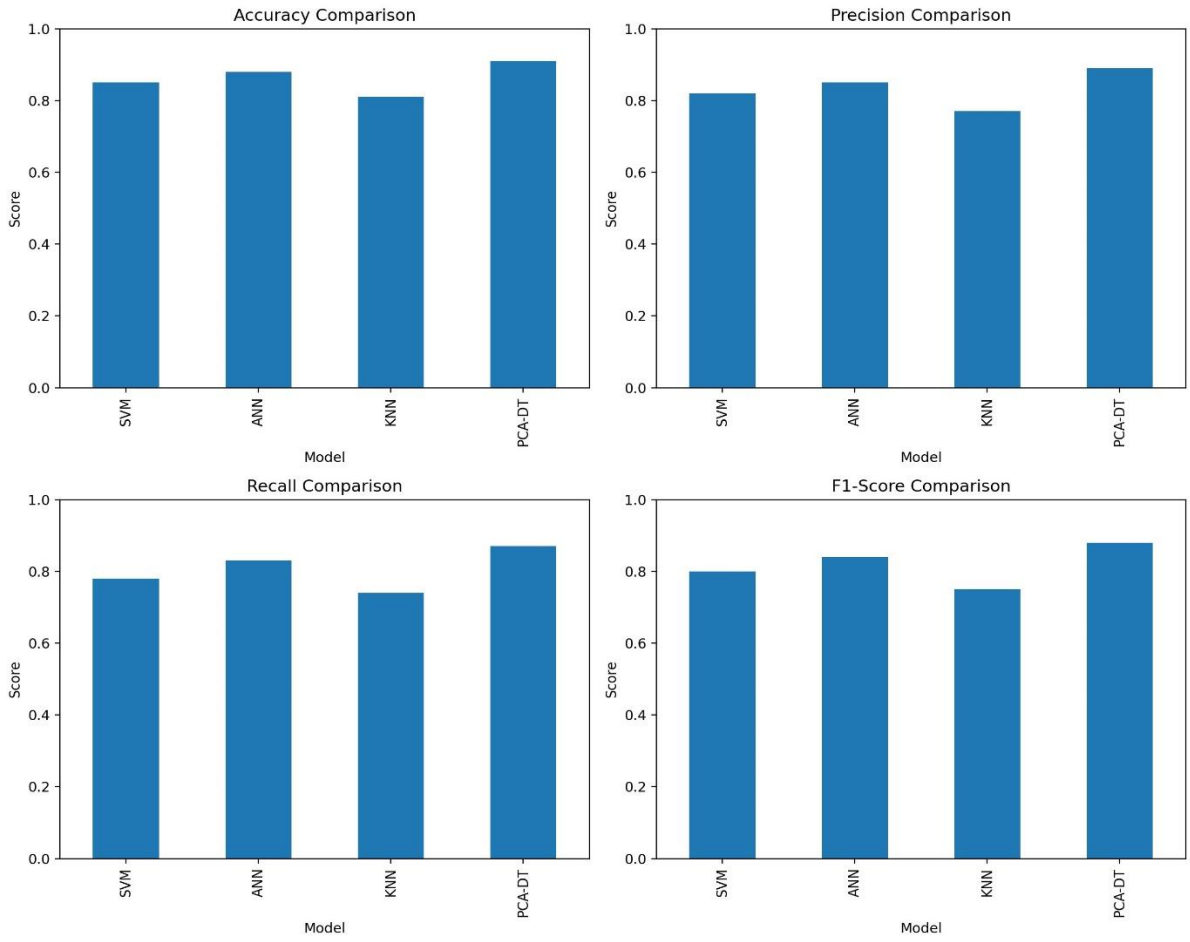

Figure 5. Comparison and performance of metric for machine learning models

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1. Accuracy Comparison:

In the banking industry maintaining high-quality data is crucial for the effectiveness of machine learning algorithms, especially in domains like risk evaluation, identifying fraudulent activities, and categorizing customers. This research evaluated the efficacy of various machine learning techniques, including SVM, ANN, KNN, and a novel PCA-Decision Trees (PCA-DT) approach, to identify the most suitable method for processing complex financial information. The innovative PCA-DT technique achieved the highest accuracy rate of 91%, surpassing SVM (85%), ANN (88%), and KNN (81%). By integrating Principal Component Analysis (PCA), the method effectively reduced dimensionality, minimizing noise and simplifying high-dimensional financial datasets. This significantly boosted the performance of the Decision Tree (DT) model, as the reduced-dimensional data enhanced prediction accuracy and efficiency without sacrificing crucial information. These findings highlight the importance of data governance in preserving high-quality data for machine learning applications in banking, particularly when combined with advanced methods like PCA-DT. By implementing data governance frameworks that ensure data integrity, security, and usability, banks can establish a robust foundation for optimizing model performance and generating reliable, precise results in critical financial operations.

2. Precision Comparison:

In the field of banking, accuracy is paramount for machine learning models, this research revealed that the PCA-Decision Tree (PCA-DT) model excelled in terms of precision, reaching the highest score of 89%. This suggests that the model produced fewer inaccurate positive predictions, thereby enhancing the reliability of its positive classifications. The ANN model followed closely with 85% precision, while SVM (82%) and KNN (87%) showed lower precision rates. The impressive precision score of PCA-DT highlights its capability to accurately identify positive cases (such as fraudulent activities or high-risk clients) with minimal mistakes. The incorporation of Principal Component Analysis (PCA) played a significant role in this outcome by eliminating noise and superfluous features, resulting in more refined data inputs and enhanced decision-making processes for the Decision Tree (DT) model.

3. Recall Comparison:

In the banking industry, recall is a crucial metric as a vital performance indicator, this study revealed that the PCA-Decision Tree (PCA-DT) model exhibited exceptional recall performance, attaining an 87% score. This high recall rate demonstrates the PCA-DT model's proficiency in accurately recognizing a substantial number of positive instances, effectively pinpointing fraudulent transactions or high-risk borrowers. The model's success in capturing a large proportion of true positives while minimizing false negatives is reflected in this impressive recall score. The incorporation of Principal Component Analysis (PCA) enhanced the model's capacity to handle complex datasets by reducing dimensionality, eliminating noise, and focusing on the most relevant features for prediction. This optimization allowed the Decision Tree (DT) to more effectively discern patterns and make accurate classifications, thereby boosting recall. In comparison, the Artificial Neural Network (ANN) achieved a recall score of 83%, showing strong but slightly lower sensitivity to positive cases than PCA-DT. Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) models trailed behind with recall scores of 78% and 74% respectively, indicating they missed more positive instances. The superior recall performance of PCA-DT underscores the importance of robust data governance in ensuring high-quality data for machine learning applications. By promoting data integrity and usability, well-structured governance frameworks contribute to the enhanced performance of sophisticated models like PCA-DT, leading to improved outcomes in critical banking operations such as fraud detection, risk management, and customer segmentation.

4. F1-Score Comparison:

The F1 score serves as a vital indicator for assessing the overall effectiveness of machine learning models, particularly in banking where both precision and recall hold significant importance. This metric offers a balanced evaluation by combining the model's capacity to accurately identify true positives while reducing false positives. In this research, the PCA-Decision Tree (PCA-DT) model exhibited the highest F1-score at 88%, showcasing its exceptional balance between precision and recall. This result indicates that PCA-DT not only successfully identified numerous positive instances (high recall) but also limited incorrect positive predictions (high precision). The PCA-DT model's top F1-score of 88% demonstrates its well-rounded performance in both precision and recall aspects. ANN closely followed with an F1-score of 84%, while SVM and KNN displayed lower balanced scores. The impressive F1-score of PCA-DT underscores its efficacy in both recognizing true positives and minimizing false positives, making it especially suitable for banking

applications such as fraud detection, credit scoring, and risk assessment. By employing Principal Component Analysis (PCA) for dimensionality reduction, the model concentrated on the most relevant features, enhancing the Decision Tree (DT) model's performance and ensuring balanced results across key metrics. ANN's close second with an F1-score of 84% indicates strong overall performance, albeit slightly less balanced compared to PCA-DT. SVM and KNN, with F1-scores of 80% and 75% respectively, exhibited weaker performance in balancing precision and recall, resulting in more trade-offs between false positives and missed true positives. The superior F1-score of PCA-DT emphasizes the importance of data governance in maintaining data quality for machine learning applications in the banking sector. With robust governance frameworks ensuring data integrity, accuracy, and usability, models like PCA-DT can operate more reliably, optimizing decision-making processes in critical banking operations.

5.CONCLUSION

As the financial sector increasingly turns to machine learning in general, and more specifically, large language models (LLMs), the scale of data being relied upon only grows larger and more complicated, making a strong case for efficient and scalable data labeling schemes. These volumes and the granularity of labeling are not feasible using traditional manual methods, both in terms of cost and scalability. In this study using Principal Component Analysis (PCA) for dimensionality reduction and Decision Trees (DT) for data classification and annotation, we propose a framework for an automatic data labeling and annotation approach that can cope with these challenges. This framework is extremely useful in enhancing the accuracy, speed, and scalability of data labeling for financial datasets. Utilizing PCA for feature extraction and DTs as automation of the annotation process, our system provides LLMs with contextually relevant, high-quality, topically labeled data. This allows the continuous and on-demand training of LLMs in order to improve their capabilities for essential financial use cases like fraud detection, risk assessment, and customer behavior analysis. The combined use of PCA and DT in the data labeling pipeline reduces resource costs for annotation while laying the groundwork towards automated annotation systems that can pave the way now, with both manual and eventual auto-scaling-up processes helping financial organizations better leverage their data.

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