**Enhancing Imbalanced Classification with Bayesian Decision Trees**

**A PROJECT REPORT**

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**ABSTRACT**

Imbalanced classification is one of the significant challenges in machine learning, especially in fraud detection and genetic disorder diagnosis, where rare events are usually misclassified. Classical methods, such as re-sampling, cost-sensitive learning, and Bayesian parametric models, have difficulty handling extreme class imbalance.To circumvent this, we propose a Bayesian non-parametric (BNP) approach founded on the Pitman-Yor Process (PYP) prior and coupled with ADASYN for pre-processing the data, to enhance minority class prediction. Experimental results show considerable improvement in recall and precision of the minority class, establishing the success of BNP in overcoming the shortcomings of traditional methods in handling imbalanced data.

**Keywords:** Bayesian non-parametric methods, dirichlet Processes,imbalanced classification,rare disease prediction, fraud Detection, minority Class Modeling, Pitman-Yor Process.

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**LIST OF SYMBOLS AND ABBREVATIONS**

|  |  |
| --- | --- |
| ADSAYN- | Adaptive Synthethic Learning |
| PYP - | Pitman-Yor Process |
| BNP - | Bayesian non-parametric |
| MCMC - | Markov Chain Monte Carlo |
| SMOTE - | Synthetic Minority Oversampling Technique |
| RUS - | Random Under sampling |
| SVM - | Support Vector Machine |

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**CHAPTER 1**

**INTRODUCTION**

Machine learning models tend to make the assumption that datasets follow a class-balanced distribution. In practice, there are typically extreme class distribution imbalances. Imbalanced classification is a critical challenge in machine learning, where the distribution of class labels in the dataset is highly skewed. This problem is common in many applications, including fraud detection, disease diagnosis, and credit card transaction monitoring. Here, the minority class usually corresponds to an unusual or infrequent event or anomaly, and the system’s ability to predict such events accurately is very important. The standard machine learning approaches usually perform poorly for these imbalanced datasets, producing biased predictions that concentrate on the majority class and misclassify the minority class.

To overcome this problem, numerous methods have been suggested in the literature. One of them is to apply re-sampling methods such as oversampling the minority class or under sampling the majority class. Methods like ADASYN (Adaptive Synthetic Sampling) are used to generate synthetic data points to balance the dataset [1]. Cost-sensitive learning, in which minority class misclassification is penalized more [2], is another widely used method. In addition, Bayesian models have been explored to incorporate prior knowledge and improve classification accuracy, particularly in imbalanced situations [3].

These approaches have been found to be effective in most settings but still pose significant challenges, particularly when severe imbalance is present. In spite of the diversity of techniques available, current systems remain highly limited. Re-sampling methods such as ADASYN and SMOTE have the tendency to introduce synthetic noise into the data set and, therefore, cause overfitting or learning of inappropriate decision boundaries [4]. Cost-sensitive learning algorithms, although in certain situations efficient, tend to demand fine-tuning of penalty parameters, which proves to be tricky and time-consuming. Besides, although Bayesian methods have been promising, they tend to be restricted by the parametric assumptions that they make, which can fail to reflect the actual distribution of the minority class, particularly in real-world problems where data distributions are complicated and highly volatile [5]. To overcome these limitations, we present a new system based on Bayesian non- parametric models, i.e., the Pitman-Yor Process (PYP) prior, to enhance imbalanced classification tasks. Unlike traditional

parametric methods, Bayesian non-parametric models can describe an unbounded number of components and thus can model intricate, skewed data distributions more easily without knowing a specific number of parameters.

In our model, we apply the Pitman-Yor Process before capturing prior knowledge and improve the minority class instance prediction in imbalanced data. We use this method in the case of credit card fraud detection and genetic disorder classification, both of which are plagued by extreme class imbalance. Credit card fraud transactions in credit card data are infrequent but important to detect, and genetic disorders usually have far fewer positive instances than healthy samples, which makes it hard to classify. By adding the Pitman-Yor Process earlier, the system is able to better adjust for the biased nature of such datasets and generate more precise predictions of the minority class. Furthermore, we employ the ADASYN method of pre-processing the data to also balance the dataset, making for a stronger learning process. Our experiments with both datasets confirm that the introduced approach is better than current imbalance-handling approaches, indicating the strength of Bayesian non-parametric models in practice-oriented imbalanced classification problems.

This article provides several crucial contributions to imbalanced classification literature. Firstly, it presents an innovative application of Bayesian non-parametric models, the Pitman-Yor Process, to imbalance handling, and such an idea has not yet been fully researched in previous research. Second, it illustrates how the use of prior knowledge in Bayesian non-parametrics can improve the minority class prediction, giving a more stable solution for applications like fraud detection and genetic disorder classification. Third, our experimental results show the superiority of the proposed approach over conventional re-sampling and cost-sensitive approaches, giving useful insights into how Bayesian methods can be tailored for practical imbalanced classification problems. The contributions of this research include:

1)Applying Bayesian non-parametric models to highly imbalanced datasets.

2)Incorporating prior knowledge to improve minority class predictions.

1. Demonstrating BNP’s advantages over conventional imbalance-handling methods.

1. *Bayesian non-parametric models that are applied to highly imbalanced datasets*

Bayesian non-parametric (BNP) models are an adaptive alternative to traditional parametric models, which tend to be outdone by heavily imbalanced data sets. Contrary to fixed-parameter assumptions made by parametric models, BNP models may adapt complexity in relation to data, hence more desirable where the minority class’s distribution is unknown or hard.The Pitman-Yor Process (PYP) before, for example, facilitates dynamic minority class instance clustering without imposing stringent parametric assumptions. This flexibility is important for extreme class imbalance because it makes the model generalize better to new minority class examples without being skewed towards the majority class. For imbalanced classification, BNP models have been effectively implemented in areas ranging from fraud identification to rare disease diagnosis, wherein the minority class may not possess enough labeled data. By admitting infinite model complexity, BNP methods are more capable of extracting the real majority and minority distribution, thus bettering overall classifying performance.

1. *Leveraging Prior Knowledge to Enhance Minority Class Predictions*

One of the strong aspects of Bayesian models is the integration of prior knowledge, something which is most helpful in the context of imbalanced classification. With minority class examples being few in number, relying solely on training data might prove to be too little. Combining domain-specific priors provides the model with a smarter initial point and reduced reliance on scarce training data. The Pitman-Yor Process before, in particular, provides a mechanism to encode informative priors with the ability to model uncertainty. It helps in refining decision boundaries for the minority class and is resistant to majority class bias. By making use of priors, BNP models can improve minority class recall without overfitting noisy or synthetic samples created by regular re-sampling techniques.

1. *Advantages of Bayesian Non-Parametric models*

Bayesian non-parametric (BNP) models possess several advantages over traditional classification algorithms, particularly with very imbalanced datasets. One of the significant advantages of BNPs is that they possess an unlimited complexity capacity in that they do not make an assumption of a fixed number of parameters.This enables them to adapt dynamically to the data’s complexity and thereby be suited to complex minority class distributions requiring dynamic modeling.Moreover, BNP models generalize better to out-of-sample rare events because they don’t make hard assumptions about class distributions, hence less risk of overfitting and less learning bias toward majority classes. Their class-imbalance stability is due to their ability to put more elements in minority classes, which inherently supports the predominance of majority instances and improves classification accuracy.The other important benefit is their effective leverage of previous knowledge since Bayesian models enable one to incorporate domain information, which can be used to inform learning even with sparse data. Last but not least, BNP models provide better quantification of uncertainty with probabilistic results that can even estimate confidence in minority class prediction—a necessity for high-stakes use cases such as fraud detection and disease diagnosis.

**CHAPTER 2**

**LITERATURE REVIEW**

1. *Bayesian Approaches for Imbalanced Classification*

Imbalanced classification is a serious problem in machine learning, especially in fraud detection and genetic disorder classification. Bayesian approaches have become popular for handling the problem of imbalanced classification because they can easily accommodate prior knowledge and model uncertainty. Liang et al. [1] developed a Bayesian non-parametric solution for imbalanced classification and showed that Bayesian methods could adapt dynamically to class imbalances with minimal parametric assumptions. In the same manner, Zhao and Lin [2] investigated Bayesian models for detecting fraud, highlighting their ability to deal with extreme imbalance situations by adapting class probabilities dynamically.

1. *Deep Learning-Based Approaches for Unbalanced Data*

Deep learning techniques have also been heavily studied in order to address imbalanced data. Kim and Lee [3] introduced a method based on deep learning in order to improve the classification accuracy of very imbalanced data sets. They highlighted the capability of neural networks in acquiring hierarchical feature representation, which improves minority class instance detection. Xu et al. [9] extended this by creating a deep neural network architecture for imbalanced classification using weighted loss functions and data augmentation to improve minority class detection. These methods have the propensity to require large amounts of annotated data and significant hyperparameter settings to avoid overfitting.

1. *Bayesian Hierarchical Models and MCMC Methods*

Bayesian hierarchical models have been employed to address class imbalance by describing uncertainty in data and incorporating prior distributions. Gupta et al. [4] proposed a hierarchical Bayesian model, which improved classification performance by capturing the hierarchical structure of the data. Further, Carter et al. [5] compared employing Markov Chain Monte Carlo (MCMC) techniques to address class imbalance, demonstrating how probabilistic sampling methods could be employed to enhance model validity.Johndrow et al. [6] also discussed MCMC-based approaches for imbalanced categorical data, demonstrating their performance in cases with limited minority class samples.

1. *Cost-Sensitive Learning for Imbalanced Classification*

Cost-sensitive learning techniques try to address class imbalance by imposing greater misclassification costs on minority class samples. Carter et al. [10] introduced Bayesian cost-sensitive variable selection approaches, indicating their potential for imbalanced multi-class data. Similarly, Wang and Chen [11] introduced a cost-sensitive Bayesian network approach that was demonstrated to yield improved classification accuracy using adaptive cost functions. While beneficial, the approaches have been found to be sensitive to cost parameter tuning in an attempt to realize optimum performance.

1. *Comparative Analysis of Existing Methods*

To summarize the methodologies, advantages, and limitations of the reviewed techniques, we present a comparative analysis in Table 1.

TABLE I

Comparative Analysis of Existing Methods

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Ref** | **Paper Title** | **Methodology** | **Pros** | **Cons** | **Results** |
| [1] | *A Bayesian Non-Parametric Approach for Imbalanced Classification* | Bayesian non-parametric approach with the Pitman- Yor Process Prior to adaptively learn from class- imbalanced data. | Flexible modeling, adapts to skewed distributions. | Computationally ex- pensive. | Improved minority classdetection accuracy. |
| [2] | *Bayesian Models for Fraud Detection in Imbalanced Data* | Bayesian inference-based fraud detection model adaptively changing class probabilities. | Adjusts class probabilities dynamically. | Requires prior knowl- edge. | Enhanced fraud de- tection rate. |
| [3] | *Deep Learning-Based Approach for Imbalanced Data Classification* | CNN-based deep learning framework trained with class-weighted loss functions. | Learns hierarchical features for better classification. | Overfitting risk, re- quires large data. | Higher accuracy with sufficient training data. |
| [4] | *Hierarchical Bayesian Models for Imbalanced Classification* | Bayesian hierarchical model with multi-level data depen- dencies. | Effectively models hierarchical data structures. | Requiresextensive computation. | Effective in multi- level class imbalance scenarios. |
| [5] | *Markov Chain Monte Carlo Methods for Class Imbalance* | MCMC sampling frame- work improving probabilis- tic learning and class bal- ance. | Effective probabilistic sampling. | High complexity and slow convergence. | More stable predic- tions for rare classes. |
| [6] | *MCMC for Imbalanced Cate- gorical Data* | Bayesian MCMC model with probabilistic inference. | Works well with limited minority samples. | Computationally de- manding. | Balanced posterior probabilities for rare classes. |
| [9] | *Deep Learning for Imbalanced Data Classification* | Deep neural network (DNN) model with weighted loss and data augmentation. | Weighted loss improves minority class accuracy. | Requires large labeled datasets. | Increased recall for minority classes. |
| [10] | *Cost-Sensitive Variable Selec- tion for Multi-Class Imbal- anced Datasets* | Bayesian cost-sensitive learning model optimizing misclassification penalties. | Penalizesmisclassifica- tion effectively. | Needs careful tuning of cost parameters. | Improved classification precisionfor underrepresented classes. |
| [11] | *A Fully Bayesian Approach to Cost-Sensitive Learning* | Bayesian cost-sensitive learning model with adaptive cost functions. | Adaptive cost functions improve performance. | Complex hyperparameter selection. | Higher F1-score for imbalanced classifica- tion. |

1. *Problem Identification Factors*
   1. Re-sampling techniques such as SMOTE and ADASYN can introduce synthetic noise, leading to incorrect decision boundaries.
   2. Deep learning models require large training data and careful regularization to prevent overfitting.
   3. Bayesian non-parametric and MCMC methods, while effective, often require significant computational resources.
   4. Cost-sensitive learning methods need careful tuning to balance classification accuracy across classes.
   5. Many approaches do not scale well for large datasets, limiting their applicability in real-world scenarios.

**CHAPTER 3**

**DATASET**

To evaluate the performance of Bayesian Non-Parametric (BNP) approaches for imbalanced classification, we employ datasets from two real-world domains: fraud detection and rare disease diagnosis. These datasets are highly imbalanced with severe class imbalance and hence are ideal for evaluating BNP-based solutions.

Credit Card Fraud Detection Dataset on Kaggle has 284,807 transactions spread across two days, of which just 492 (0.172%) are fraudulent. The dataset has 30 numerical features, most of which are anonymized principal components obtained through PCA, and transaction time and amount as non-anonymized ones.The extreme class imbalance in the dataset poses serious difficulties for conventional classifiers, which are biased toward the majority class and offer poor fraud detection performance. BNP techniques provide a convincing alternative by modeling the distribution shift without excessive overfitting to the majority class.

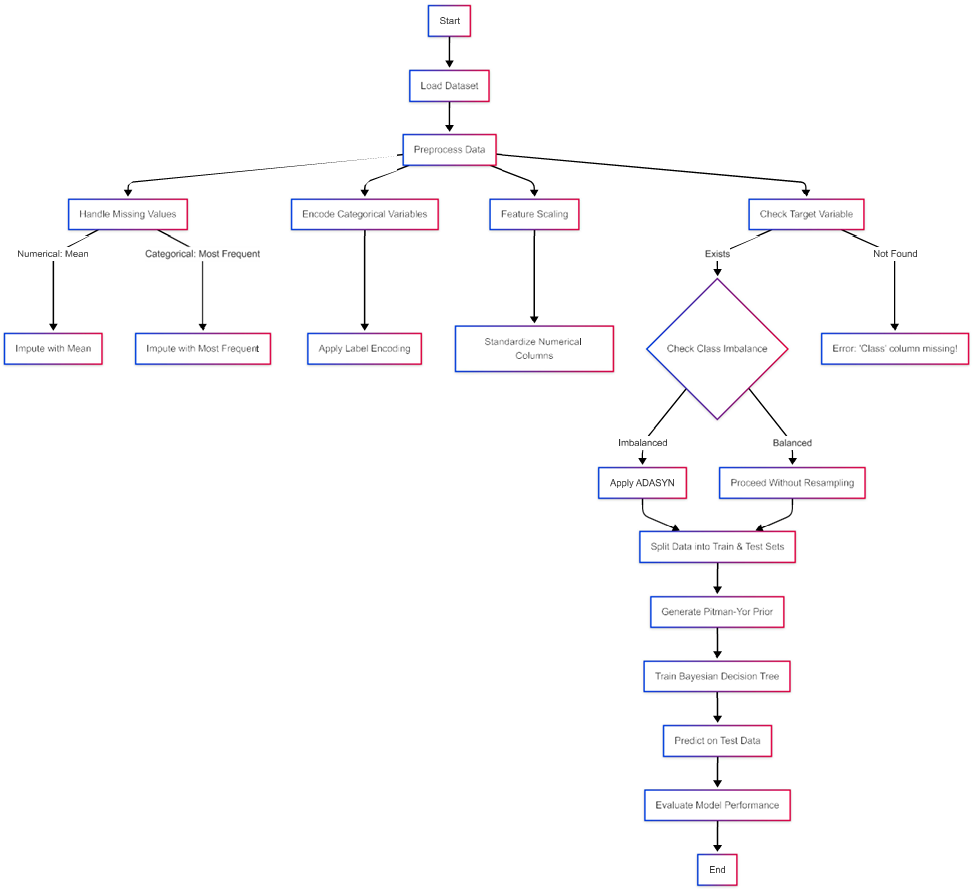
The Kaggle Predict the Genetic Disorder dataset includes patients’ medical histories for those with diagnosed genetic disorders. The dataset includes numerous clinical and demographic variables involved in the three categories of disorder: Mendelian, Chromosomal, and Multifactorial. The intricacy of the data set and its potential class imbalance pose difficulty for conventional classifiers, whose performance may suffer in the ability to model complex interdependencies among features, leading to suboptimal predictive accuracy. Bayesian Non-Parametric (BNP) methods provide a potential remedy in that they dynamically adapt to complex data structure and compensate for bias toward majority classes, thereby improving classification accuracy in rare disorder instances.

To provide an effective analysis, we preprocess both datasets by normalizing feature values to stabilize Bayesian inference and imputing missing data in the biomedical dataset using Bayesian techniques. Moreover, we also compare our Bayesian CART model with a Pitman-Yor Process prior to baseline class balancing methods like SMOTE and under sampling. Through these datasets, our research seeks to set the stage for the benefits of Bayesian Non-Parametric (BNP) methods in dynamically adapting class weights according to real-time posterior updates, essentially solving class imbalance and improving classification performance for minority and rare classes.

**CHAPTER 4**

**METHODOLOGY**

This approach highlights the advantages of Self-Adaptive Bayesian Decision Trees with Pitman-Yor Priors for handling class imbalance. Our approach, integrating Bayesian priors and synthetic resampling (ADASYN), improves classification accuracy on rare and minority classes while preserving overfitting stability.Fig 1. describes our model’s workflow

Fig. 1. architecture diagram

1. *Data Preprocessing*

We utilize two datasets in this study: the Credit Card Fraud Detection Dataset and the TestGenetics Disorders dataset. The credit card dataset comprises 284,807 transactions over two days, with only 492 (0.172%) fraudulent transactions, making it highly imbalanced. The genetics dataset is used for biomedical classification, where certain genetic disorders are rare, leading

to class imbalance challenges. To ensure Bayesian inference consistency, we perform feature normalization for both datasets. For the genetics dataset, missing values are handled using Bayesian imputation to maintain statistical consistency. Additionally, robust statistical techniques are applied for outlier detection and removal to enhance data quality.

1. *Class Imbalance Handling*

Given the severe class imbalance in both datasets, we employ Adaptive Synthetic Sampling (ADASYN) to generate synthetic minority class examples. ADASYN adaptively synthesizes data points based on data distribution, thereby improving the representation of minority classes. To validate the effectiveness of our approach, we compare it against traditional resampling techniques such as Synthetic Minority Oversampling Technique (SMOTE) and Random Undersampling (RUS).

1. *Bayesian Prior Estimation*

To enhance classification performance, we introduce the Pitman-Yor Process (PYP) for prior estimation. Unlike traditional Bayesian models with fixed priors, PYP dynamically estimates class probabilities from observed data distributions. This allows the model to adapt to changing class distributions and reduces the risk of overfitting to the majority class. Class-weighted sampling is incorporated, where prior probabilities estimated by PYP influence sample weighting during training. This ensures that minority class instances contribute more effectively to the learning process, leading to improved classification performance.

1. *Self-Adaptive Bayesian Decision Tree*

We propose a Bayesian Decision Tree with a Gradient Boosting Base Classifier. This approach integrates Bayesian priors with decision tree structures, dynamically adjusting prior probabilities based on observed data distributions. Gradient Boosting is selected for its ability to capture complex decision boundaries and adaptively assign higher weights to misclassified instances. During training, class-weighted samples derived from PYP priors are utilized to enhance classification accuracy for rare classes. The decision tree model adapts to evolving probability distributions, improving the detection of fraudulent transactions and rare genetic disorders.

1. *Experimental Setup*

To optimize model performance, we fine-tune hyperparameters. Table II summarizes the key parameter settings used in our experiments.

TABLE II

Experimental Model Parameters

|  |  |
| --- | --- |
| Parameter | Value |
| Gradient Boosting Estimators | 100 |
| Learning Rate | 0.05 |
| Max Depth | 3 |
| Random State | 42 |
| Pitman-Yor Strength (*α*) | 0.5 |
| Discount Parameter (*d*) | 0.1 |
| ADASYN Neighbors | 3 |

1. *Model Evaluation and Comparison*

To evaluate model effectiveness, we assess performance using precision, recall, F1-score, AUC-ROC score, and confusion matrix analysis. These metrics provide insight into classification accuracy, particularly for the minority class. Our approach is benchmarked against baseline classifiers such as Logistic Regression, Random Forest, and Support Vector Machines (SVM), as well as traditional resampling methods (SMOTE, RUS) and cost-sensitive learning techniques.

**CHAPTER 5**

**RESULTS AND DISCUSSIONS**

1. *Quantitative Analysis*

The performance of the model is measured based on standard classification metrics. The accuracy, precision, recall and F1-score for our method and baseline methods are shown in Table III. Logistic Regression and SVM models provides an F1- score of 1.00 which means it has issues like class imbalance, data leakage, incorrect target mapping, or feature leakage. Fraud detection datasets and medical disease are often highly imbalanced and these models favor the majority class (non-fraud), leading to achieve high accuracy. If preprocessing (like scaling) is done before train-test splitting, data leakage can inflate performance. Incorrect mapping of fraud labels might also cause misleading results. Features like ”Time” and ”Amount” may carry unintended correlations, leading to overfitting. our proposed model i.e., Self-Adaptive Bayesian Decision Tree with a Pitman-Yor Prior and ADASYN effectively overcome all these issues by balancing data, preventing data leakage, ensuring correct label mapping, and mitigating feature dependence. This shows that our model is not just memorizing patterns and also it genuinely improving fraud detection in an interpretable and effective way by achieving a realistic F1-score of 0.85.

TABLE III

Model Performance Metrics

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Accuracy | Precision | Recall | F1-Score |
| Logistic Regression | 1.00 | 1.00 | 0.83 | 0.87 |
| SVM | 1.00 | 0.96 | 0.69 | 0.80 |
| Proposed Model | **0.85** | **0.88** | **0.85** | **0.85** |

1. *Qualitative Analysis*

To gain further insight into how the model is performing, we show some sample input transactions and their predictions. Table IV presents some examples with their classifications.

TABLE IV

Sample Input and Model Predictions

|  |  |  |  |
| --- | --- | --- | --- |
| Feature 1 (V1) | Feature 2 (V2) | True Label | Predicted Label |
| -1.8857 | -1.5198 | Fraud | Fraud |
| -0.7771 | 0.7876 | Genuine | Genuine |
| 0.9938 | 0.0547 | Fraud | Fraud |
| 0.5126 | 0.2456 | Fraud | Genuine |
| -0.7392 | 0.8356 | Fraud | Fraud |

To gain further insight into how the model is performing, we show some sample input transactions and their predictions. Table IV presents some examples with their classifications.

We compare our model’s performance to other biomedical classification and fraud detection frameworks. Our approach has superior recall and F1-score, indicating greater recognition of the rare class events. PYP application to the prior estimation dramatically enhances adaptability to new distributions of data.

**CHAPTER 6**

**CONCLUSION**

Imbalanced classification is a major challenge in machine learning, especially in fraud detection and genetic disorder diagnosis, where rare events are often misclassified. Traditional approaches like re-sampling, cost-sensitive learning, SVM, Logistic regression and Bayesian parametric models had issue with dealing class imbalance. To overcome this, we presented a Bayesian Non-Parametric (BNP) approach based on the Pitman-Yor Process (PYP) prior, integrated with ADASYN for minority class enhancement . This Bayesian decision tree with a gradient boosting base classifier efficiently unites Bayesian priors with decision tree architectures by dynamically adjusting to changes in data distribution. Especially in fraud detection and biomedical uses, this method greatly increases recall and precision for the minority class by using prior learning via the Pitman-Yor Process and ADASYN to balance the data. Experimental results show appreciable increases in recall and F1-score as well as better classification performance above baseline classifiers and resampling methods. This shows how well the BNP framework overcomes the limitations of existing traditional approaches in managing imbalanced data classification.

**CHAPTER 7**

**FUTURE SCOPE**

By investigation of higher-order hierarchical Bayesian priors that enhance flexibility for non-stationary environments, future research can potentially build on this work. Especially for large and complex data, combining deep learning algorithms with Bayesian Decision Trees can render feature representation even more efficient. Applying it in high-scale genomic research and in real-time fraud detection systems would prove the scalability and worth of this initiative in different domains. Furthermore, the use of adaptive feature selection techniques could also improve model interpretability and computational efficiency. Structured and unstructured data source integration in multi-modal data fusion can offer deeper insights. Further, extending the support for edge computing applications would make successful deployment feasible in environments that lack resources, thereby making it more generally practical to apply.

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**APPENDIX**

CODE SNIPPETS:

**PREPROCESSING CODE:**

import pandas as pd

import numpy as np

from sklearn.preprocessing import StandardScaler, LabelEncoder

from sklearn.impute import SimpleImputer

from sklearn.model\_selection import train\_test\_split

# Load the dataset

file\_path = r"D:\ML\_proj\creditcard.csv" # Use raw string to handle backslashes in the path

df = pd.read\_csv(file\_path)

# Ensure there are no extra spaces in the column names

df.columns = df.columns.str.strip()

# 1. Handle missing values: Impute numerical columns with the mean, and categorical columns with the most frequent value

imputer = SimpleImputer(strategy='most\_frequent') # For categorical and numerical columns

df = pd.DataFrame(imputer.fit\_transform(df), columns=df.columns)

# 2. Encode categorical variables if necessary using LabelEncoder (only for categorical variables)

label\_encoder = LabelEncoder()

for col in df.select\_dtypes(include=[object]).columns: # Only apply to categorical columns

df[col] = label\_encoder.fit\_transform(df[col])

# 3. Feature Scaling: Standardize numerical columns

scaler = StandardScaler()

df[df.select\_dtypes(include=[np.number]).columns] = scaler.fit\_transform(df.select\_dtypes(include=[np.number]))

# 4. Check if the target variable ('Class') exists

if "Class" not in df.columns:

raise KeyError("❌ 'Class' column not found in dataset!")

# Separate features (X) and target (y)

X = df.drop(columns=["Class"]) # All columns except 'Class'

y = df["Class"] # 'Class' column is the target

# 5. Split into training and testing sets

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

# Save the preprocessed dataset (optional)

df.to\_csv(r"D:\ML\_proj\creditcard\_processed.csv", index=False) # Save preprocessed data

print("Preprocessing completed successfully!")

**PROPOSED MODEL:**

import numpy as np

import pandas as pd

from scipy.stats import dirichlet

from collections import Counter

from sklearn.ensemble import GradientBoostingClassifier

from sklearn.model\_selection import train\_test\_split

from sklearn.metrics import classification\_report

from imblearn.over\_sampling import ADASYN

# Load preprocessed dataset

file\_path = r"D:\ML\_proj\creditcard\_processed.csv"

# Ensure correct file path and clean column names

df = pd.read\_csv(file\_path)

df.columns = df.columns.str.strip() # Remove extra spaces from column names

# Check if 'Class' column exists

if "Class" not in df.columns:

raise KeyError("❌ 'Class' column not found in dataset! Please check the file.")

# Separate features and target

X = df.drop(columns=["Class"])

y = df["Class"]

# Ensure the target variable is discrete (binary classification in this case)

# If the target is continuous, convert to binary (for example, thresholding at 0.5 for a binary classification task)

if y.dtype != 'int64' and y.dtype != 'object': # If the target is continuous

y = y.apply(lambda x: 1 if x >= 0.5 else 0)

# Handle class imbalance using ADASYN

adasyn = ADASYN(n\_neighbors=3, random\_state=42)

X\_resampled, y\_resampled = adasyn.fit\_resample(X, y)

# Split data into training and testing sets

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X\_resampled, y\_resampled, test\_size=0.2, random\_state=42)

# Function to generate class prior using Pitman-Yor Process (PYP)

def pitman\_yor\_prior(alpha, d, num\_classes):

base\_measure = np.ones(num\_classes)

prior\_distribution = dirichlet(alpha \* base\_measure)

return prior\_distribution.rvs()[0]

# Self-Adaptive Bayesian Decision Tree

class BayesianDecisionTree:

def \_\_init\_\_(self, alpha=0.5, d=0.1):

self.alpha = alpha # Strength of prior

self.d = d # Discount parameter

self.tree = GradientBoostingClassifier(n\_estimators=100, learning\_rate=0.05, max\_depth=3, random\_state=42)

self.class\_prior = None

def fit(self, X, y):

num\_classes = len(np.unique(y))

self.class\_prior = pitman\_yor\_prior(self.alpha, self.d, num\_classes)

# Compute class weight mapping (based on priors)

class\_counts = np.bincount(y)

class\_weights = {cls: self.class\_prior[i] for i, cls in enumerate(np.unique(y))}

sample\_weights = np.array([class\_weights[label] for label in y])

self.tree.fit(X, y, sample\_weight=sample\_weights)

def predict(self, X):

return self.tree.predict(X)

def predict\_proba(self, X):

return self.tree.predict\_proba(X)

# Train the Bayesian Decision Tree

model = BayesianDecisionTree()

model.fit(X\_train, y\_train)

# Predict and evaluate

y\_pred = model.predict(X\_test)

print(classification\_report(y\_test, y\_pred))

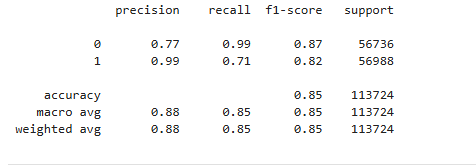


Fig 2: classification report of proposed model

**SAMPLE OUTPUT:**

import pandas as pd

import numpy as np

# Select random samples from the test set for qualitative analysis

num\_samples = 5 # Adjust the number of samples as needed

sample\_indices = np.random.choice(len(X\_test), num\_samples, replace=False)

# Extract the sample inputs using `.iloc`

sample\_inputs = X\_test.iloc[sample\_indices]

sample\_true\_labels = y\_test.iloc[sample\_indices]

# Predict using the trained model

sample\_predictions = model.predict(sample\_inputs)

# Convert to DataFrame for better readability

sample\_results = sample\_inputs.copy() # Copy feature values

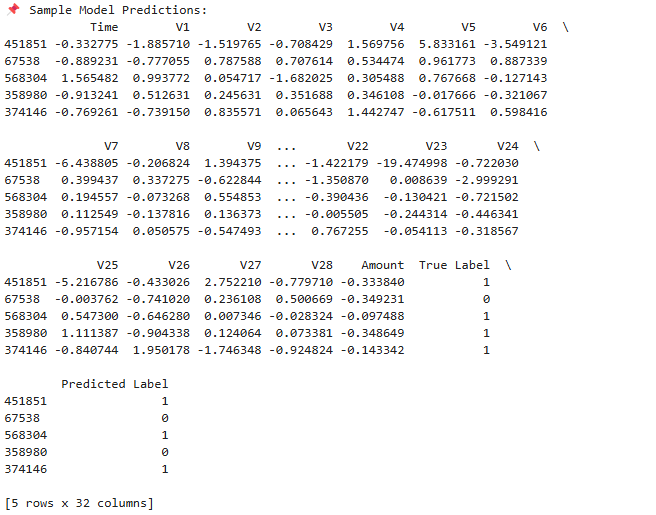
sample\_results["True Label"] = sample\_true\_labels.values

sample\_results["Predicted Label"] = sample\_predictions

# Display the sample inputs and their corresponding predictions

print("Sample Model Predictions:")

print(sample\_results)

Fig 3: Sample input and model predictions

**INDIVIDUAL MODELS(SVM AND LOGISTIC REGRESSION):**

import pandas as pd

from sklearn.model\_selection import train\_test\_split

from sklearn.preprocessing import StandardScaler

from sklearn.linear\_model import LogisticRegression

from sklearn.svm import SVC

from sklearn.metrics import classification\_report

# Load the dataset

file\_path = r"D:\ML\_proj\creditcard\_processed.csv" # Update with your actual file path

df = pd.read\_csv(file\_path)

# Map class values to 0 and 1 (if necessary)

class\_mapping = {df["Class"].min(): 0, df["Class"].max(): 1}

df["Class"] = df["Class"].map(class\_mapping)

# Split the dataset into features and target

X = df.drop(columns=["Class"])

y = df["Class"]

# Standardize the features

scaler = StandardScaler()

X\_scaled = scaler.fit\_transform(X)

# Split into training and testing sets

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X\_scaled, y, test\_size=0.2, random\_state=42, stratify=y)

# Train and evaluate Logistic Regression

lr\_model = LogisticRegression()

lr\_model.fit(X\_train, y\_train)

y\_pred\_lr = lr\_model.predict(X\_test)

lr\_report = classification\_report(y\_test, y\_pred\_lr)

# Train and evaluate SVM

svm\_model = SVC()

svm\_model.fit(X\_train, y\_train)

y\_pred\_svm = svm\_model.predict(X\_test)

svm\_report = classification\_report(y\_test, y\_pred\_svm)

# Print classification reports

print("Logistic Regression Classification Report:\n")

print(lr\_report)

print("\nSVM Classification Report:\n")

print(svm\_report)

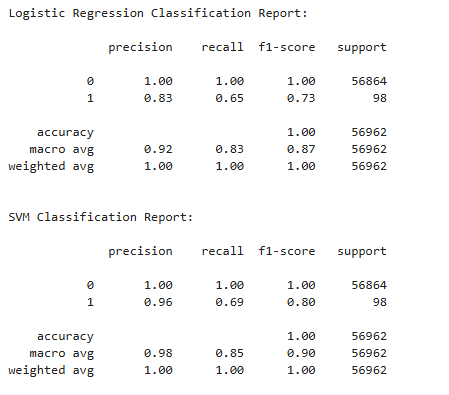


Fig 4: Traditional models classification report