**Mitigating Algorithmic Bias in Credit Scoring: A CNN-SMOTE Framework**

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**ABSTRACT**

Algorithmic bias in artificial intelligence (AI) systems has raised significant ethical concerns, particularly in critical applications such as credit scoring, where fairness and accuracy are paramount. This study proposes a novel framework that integrates Convolutional Neural Networks (CNN) with the Synthetic Minority Oversampling Technique (SMOTE) to address data imbalance and mitigate algorithmic bias. The approach leverages CNN's ability to capture complex nonlinear relationships within structured credit data while employing SMOTE to generate synthetic samples for underrepresented classes, ensuring a balanced training dataset.

**Keywords:** Algorithmic bias, **Fairness**,Random Forest, Convolutional Neural Networks (CNN), Synthetic Minority Oversampling Technique (SMOTE)…

By incorporating fairness-aware metrics and optimization strategies, the proposed framework not only improves predictive accuracy but also promotes equitable decision-making. Experimental evaluations on real-world credit scoring datasets demonstrate that this hybrid method outperforms traditional models, achieving higher classification performance while reducing disparities across demographic groups. This research highlights the potential of combining deep learning and oversampling techniques to build fairer and more transparent AI systems, paving the way for ethical advancements in financial decision-making.

1. **IntroductioN**

Algorithmic decision-making systems are increasingly being used in sensitive domains, such as financial credit scoring, healthcare, and recruitment. These systems leverage artificial intelligence (AI) and machine learning (ML) techniques to process vast amounts of data, aiming to deliver efficient and accurate predictions. However, a growing concern in these systems is the presence of algorithmic bias, where predictions or decisions unfairly disadvantage certain groups due to imbalanced training data or biased model architectures[1]. In the context of credit scoring, algorithmic bias may result in unfair lending practices, exacerbating inequalities among demographic groups and raising ethical and legal concerns.

Data imbalance is a prominent factor contributing to algorithmic bias, especially in credit datasets, where the number of "good credit" samples often significantly outweighs the "bad credit" samples. Traditional machine learning algorithms tend to prioritize accuracy on the majority class, leading to poor performance on the minority class, which often represents underprivileged groups. Consequently, there is a pressing need for methodologies that not only improve prediction accuracy but also ensure fairness across all demographic groups[2].

This study proposes a novel framework that combines Convolutional Neural Networks (CNN) and the Synthetic Minority Oversampling Technique (SMOTE) to address these challenges. CNNs are widely recognized for their ability to capture complex, nonlinear relationships in data, making them particularly effective in tasks involving high-dimensional or structured datasets, such as credit scoring. SMOTE, on the other hand, is a powerful oversampling technique that generates synthetic samples for the minority class, mitigating data imbalance and promoting fairer training[2].

The proposed framework goes beyond traditional approaches by integrating fairness-aware evaluation metrics and optimization strategies, ensuring both accuracy and equity in predictions. This paper explores the applicability of this method on real-world credit datasets, demonstrating its potential to outperform baseline models while reducing disparities in predictive performance across demographic groups[3].

The research aims to contribute not only to the technical advancement of AI in financial decision-making but also to the broader discourse on building ethical and fair AI systems[4]. By addressing both accuracy and fairness, this study sets a foundation for the development of transparent and equitable credit scoring models that can be adopted across the financial sector[5].

1. **Materials and DISCUSSIOn**
2. **Data Description**

The study utilizes a publicly available real-world credit scoring dataset, which includes features such as income, age, employment status, loan amount, and credit history. The target variable is binary, indicating creditworthiness, with 1 representing "good credit" and 0 representing "bad credit." Notably, the dataset is highly imbalanced, with the majority of samples labeled as "good credit[6]." To ensure reproducibility, the data undergoes preprocessing steps, including handling missing values through median imputation, normalizing numerical features to a range of [0, 1], encoding categorical variables using one-hot encoding, and splitting the dataset into training (80%) and testing (20%) sets.

### Synthetic Minority Oversampling Technique (SMOTE)

SMOTE addresses class imbalance by generating synthetic samples for the minority class. The algorithm creates synthetic data points along the line segments connecting minority class samples and their k-nearest neighbors[7][8].

#### **Algorithm: Synthetic Minority Over-sampling Technique (SMOTE)**

**Input:**

* **A set of minority class samples, denoted as** $X\_{minority}$**.**
* **The desired number of synthetic samples to generate, denoted as** $N$**.**
* **The number of nearest neighbors to consider, denoted as** $k$**.**

**Output: A synthetic dataset with a balanced class distribution.**

Steps:

* For each sample $x\_{i }\in X\_{minority}$: Identify its k-nearest neighbors within the minority class using a distance metric (e.g., Euclidean distance).
* Generate synthetic samples:

For each synthetic sample to be generated:

a. Randomly select one of the k-nearest neighbors, denoted as $x\_{neighbor}$.

b. Generate a synthetic sample $x\_{synthetic}$ using the formula:

$$x\_{synthetic}=x\_{i}+λ.\left(x\_{neighbor}-x\_{i}\right),$$

where λ is a random number in the range [0,1].

* Update the dataset: Append each generated synthetic sample $x\_{synthetic}$ to the minority class dataset $X\_{minority}$.
1. **Convolutional Neural Network (CNN)**

CNNs are powerful architectures for learning complex patterns in structured or high-dimensional data. The proposed CNN architecture processes tabular credit data by reshaping it into a 2D matrix format[8].

**CNN Architecture:**

* **Input Layer**: Accepts reshaped tabular features (e.g., 10 features into a 2x5 grid).
* **Convolutional Layer**: Applies 16 filters (size 2x2) with ReLU activation.
* **Pooling Layer**: Max-pooling with a 2x2 window to reduce dimensionality.
* **Flatten Layer**: Converts the feature map into a 1D vector.
* **Dense Layers**: Two fully connected layers (64 and 32 neurons, ReLU activation).
* **Output Layer**: A single neuron with sigmoid activation for binary classification[9].

The CNN is trained using binary cross-entropy loss and optimized using the Adam optimizer with a learning rate of 0.001.

Pseudocode:
*Input: Preprocessed training dataset (X\_train, y\_train), SMOTE-applied data (X\_smote, y\_smote)*

*Output:Input: Preprocessed training dataset (X\_train, y\_train), SMOTE-applied data (X\_smote, y\_smote)*

*Output: Trained CNN model*

*1. Initialize CNN architecture with specified layers*

*2. Preprocess X\_train using SMOTE to balance classes*

*3. Split data into mini-batches*

*4. For each epoch:*

 *- For each mini-batch:*

 *- Forward pass: Compute predictions*

 *- Compute loss: Binary cross-entropy*

 *- Backward pass: Update weights using Adam optimizer*

*5. Evaluate model on test set Trained CNN model*

1. **Combining SMOTE with CNN**

The integration of SMOTE and CNN is a robust approach designed to address class imbalance while leveraging the ability of Convolutional Neural Networks (CNNs) to capture complex relationships within the data[10]. This methodology involves three key steps to ensure an effective and fair classification process.

First, SMOTE preprocessing is applied to tackle the class imbalance. Synthetic Minority Over-sampling Technique (SMOTE) is used to generate synthetic samples for the minority class by interpolating between existing samples. This process results in a balanced dataset where both the minority and majority classes have equal representation, thereby mitigating the issue of bias introduced by imbalanced data[11][12].

Next, the CNN training process utilizes the balanced dataset. The CNN model is trained to extract intricate patterns and features from the input data, ensuring that both classes contribute equally to the learning process. By doing so, the model becomes more robust in distinguishing between classes, improving its overall performance[13].

Finally, a fairness-aware evaluation is conducted to assess the model’s performance comprehensively. In addition to traditional metrics such as accuracy, precision, and recall, fairness metrics like demographic parity and equalized odds are calculated[14]. These fairness metrics help evaluate whether the model performs equitably across different subgroups, ensuring that no class or demographic is unfairly disadvantaged.

This combination of SMOTE and CNN provides a balanced, accurate, and fair framework for addressing imbalanced classification problems, particularly in scenarios where fairness is as critical as model performance.

1. **Experimental Results**

**Performance Metrics:**

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Figure Performance Metrics

The framework’s effectiveness is evaluated using:

* **Accuracy**: Overall correctness of predictions.
* **Precision, Recall, F1-score**: Focused on the minority class.
* **Fairness Metrics**: Demographic parity and equalized odds to measure bias reduction.

Table 1 : Evaluation of the effectiveness of framework

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **Accuracy** | **F1-score (Minority Class)** | **Demographic Parity** |
| Baseline (No SMOTE) | 85.4% | 62.3% | 0.67 |
| SMOTE + CNN | 91.2% | 79.8% | 0.91 |

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Figure 2 State During Training

**Insights:**

The use of SMOTE significantly improves the representation of the minority class, resulting in higher F1-scores and better overall classification performance. Furthermore, fairness metrics indicate a reduction in disparities between demographic groups, demonstrating the effectiveness of this approach in mitigating bias. Additionally, the combination of CNN and SMOTE shows strong generalization capabilities, achieving high accuracy on unseen test data and validating its practical applicability in addressing imbalanced datasets.

**Applications in Credit Scoring:**

The proposed CNN-SMOTE framework has profound implications in the field of credit scoring. It promotes fair lending practices by reducing bias against underrepresented groups, ensuring more equitable access to credit for all applicants. The approach aligns with regulatory compliance standards, such as the fairness requirements outlined in the EU AI Act and similar global regulations, fostering transparency and accountability in AI systems. [15][16]Additionally, the framework enhances business impact by improving default prediction accuracy, thereby minimizing financial risk for lenders and optimizing decision-making processes.

1. **Conclusion**

The integration of Convolutional Neural Networks (CNN) and Synthetic Minority Oversampling Technique (SMOTE) presents a promising solution to address the dual challenges of data imbalance and algorithmic bias in credit scoring. By leveraging CNN’s capability to extract complex patterns and SMOTE’s ability to balance class distributions, the proposed framework achieves significant improvements in both predictive performance and fairness metrics.

Experimental results demonstrate that the CNN-SMOTE framework not only enhances the accuracy and F1-score for minority classes but also reduces disparities across demographic groups, promoting equitable decision-making[17]. This dual benefit positions the framework as a valuable tool for developing ethical AI systems in finance, particularly in areas where fairness is paramount, such as credit scoring[18].

Beyond credit scoring, this methodology has the potential to be adapted to other domains with imbalanced datasets and fairness concerns, including healthcare, fraud detection, and risk assessment. Future research could explore incorporating additional fairness-aware techniques, explainability methods, and real-time deployment scenarios to further enhance the practical applicability and transparency of the framework. In doing so, this study contributes to the broader goal of building responsible and trustworthy AI systems in critical decision-making domains.

***Authors’ contributions***

*This work was carried out in collaboration among all authors. All authors read and approves the final manuscript.*

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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Details of the AI usage are given below:

1.

2.

3.

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