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Addressing Class Imbalance in Agriculture Commodity Price Prediction Using Jellyfish-Optimized SMOTE: A Dynamic and Robust Approach

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ABSTRACT: Handling class imbalance is a critical challenge in predictive modeling for agriculture commodity price datasets, where minority class samples are often underrepresented. Traditional techniques, such as oversampling with Synthetic Minority Oversampling Technique (SMOTE) and cost-sensitive learning, struggle to achieve a balance between mitigating overfitting and preserving meaningful data structures. These methods often rely on static parameter settings, leading to suboptimal results when dealing with highly skewed or high-dimensional datasets. This study proposes a novel approach that integrates the Jellyfish Search Algorithm (JFSA) with SMOTE to address the class imbalance problem effectively. JFSA, inspired by the dynamic movements of jellyfish in the ocean, is utilized to optimize the critical parameters of SMOTE, including oversampling ratios and the number of nearest neighbors. By dynamically tuning these parameters, the proposed JFSA-SMOTE method generates synthetic samples that better represent the underlying data distribution while avoiding over-replication or noise introduction. Extensive experiments on agriculture commodity price datasets showcase the superiority of the JFSA-SMOTE approach over traditional methods, including standard SMOTE, ADASYN, and cost-sensitive classifiers. The results reveal significant improvements in model accuracy, F1-score, and AUC-ROC, particularly for minority classes.

1. INTRODUCTION

Predictive modeling in agriculture, particularly commodity price forecasting, plays a critical role in optimizing resource allocation, supporting policy decisions, and ensuring economic stability [1]. However, one of the most persistent challenges in this domain is the issue of class imbalance within datasets. Imbalanced data, where minority class samples are underrepresented compared to majority classes, often leads to biased predictions, undermining the performance of machine learning models [2]. This problem is particularly pronounced in agricultural commodity price datasets, where factors such as seasonality, regional variations, and market dynamics contribute to skewed class distributions.

Traditional methods to address class imbalance, such as oversampling techniques like the Synthetic Minority Oversampling Technique (SMOTE) [3, 4] and cost-sensitive learning approaches, have achieved varying degrees of success. Although SMOTE and its variants generate synthetic samples to augment minority classes, these methods often rely on static parameter settings, which can introduce noise or fail to capture complex data distributions. Moreover, cost-sensitive learning methods, although promising, are highly dependent on accurate cost matrices, which are challenging to determine in real-world scenarios. Consequently, these approaches frequently struggle when applied to highly skewed or high-dimensional datasets, leading to suboptimal predictive performance.

To overcome these limitations, this study proposes an innovative solution that integrates the Jellyfish Search Algorithm (JFSA) [5] with SMOTE. Inspired by the adaptive and dynamic behavior of jellyfish in their natural habitat, the JFSA offers a robust optimization mechanism capable of tuning critical parameters in SMOTE, such as oversampling ratios and the number of nearest neighbors. By dynamically adjusting these parameters, the proposed JFSA-SMOTE method ensures the generation of synthetic samples that are both representative of the underlying data distribution and devoid of over-replication or noise.

The contributions of this study are as follows:

- Development of the JFSA-SMOTE framework to dynamically optimize synthetic sample generation for addressing class imbalance in agricultural datasets.
- Extensive experimentation was conducted on real-world agricultural commodity price datasets to evaluate the effectiveness of the proposed approach against traditional methods, including standard SMOTE, ADASYN, and cost-sensitive classifiers.
- The demonstration of significant performance improvements in terms of accuracy, F1-score, and AUC-ROC, particularly for minority classes, underscores the robustness and practical applicability of the JFSA-SMOTE method.

By addressing the challenges of class imbalance through an adaptive and dynamic framework, this study contributes to the advancement of predictive modeling in agriculture, paving the way for more reliable and equitable decision-making processes in this critical sector.

2. RELATED WORKS

Recent studies have explored metaheuristic-driven oversampling to address class imbalance. Desuky et al. [6] combined single-point crossover with JFSA to generate diverse and noise-free synthetic samples, outperforming SMOTE and ADASYN. Kumar et al. [7] proposed FF-SMOTE, integrating the Firefly Algorithm with SMOTE for dynamic ratio and neighbor selection, improving accuracy under severe imbalance. Hashim [8] applied Ant Colony Optimization (ACO) to guide minority sample selection, reducing noise and enhancing balance. Similarly, Patel and Jadhav [9] optimized SMOTE using PSO and GA with neural networks and decision trees, achieving notable gains in precision, F1-score, and overall robustness.

Chen et al. [10] demonstrated that integrating SMOTE with CNNs effectively addresses class imbalance in large-scale datasets by generating synthetic samples for minority classes, leading to better feature representation and improved performance across metrics like accuracy, recall, and F1-score. Similarly, Zhang et al. [11] applied SMOTE to agri-food datasets and reported notable gains in accuracy, precision, recall, and F1-score, highlighting its adaptability in domain-specific imbalance issues. Extending this line of work, Ahmed and Gupta [12] developed a machine learning-based commodity price prediction system that not only forecasts prices but also incorporates imbalance-handling strategies, ensuring more reliable and accurate predictions in agricultural datasets.

3. MATERIALS AND METHODS

The JFSA-SMOTE method works on the agriculture dataset by dynamically optimizing the synthetic oversampling process to address class imbalance. Using the Jellyfish Search Algorithm (JFSA), parameters such as oversampling ratio and the number of nearest neighbors are adaptively tuned to generate high-quality synthetic samples for the minority class. JFSA mimics jellyfish behavior in the ocean, alternating between swarm movement and ocean current following, to explore the feature space efficiently and find the optimal oversampling parameters. This ensures that the generated synthetic samples align closely with the true distribution of the minority class. By applying JFSA-SMOTE, the imbalance in the agriculture dataset, which includes features like market dynamics, environmental factors, and seasonal patterns, is mitigated.

A. Deep Embedded Clustering (DEC) [13, 14]

Deep Embedded Clustering is a modern approach that integrates clustering with deep learning by jointly learning feature representations and cluster assignments. Unlike traditional clustering methods, DEC leverages a neural network (typically an autoencoder) to reduce high-dimensional data into a compact and meaningful latent space, where clustering becomes more effective. During training, DEC optimizes a loss function that minimizes the reconstruction error of the autoencoder while

simultaneously refining cluster centroids to align with data points in the latent space. This dual optimization ensures that the network learns both discriminative features and well-separated clusters. DEC is particularly effective for complex datasets, such as images, text, or time-series data, where traditional methods struggle with noisy or non-linear relationships. Its ability to adaptively learn features while clustering makes it a robust choice for high-dimensional, unstructured data.

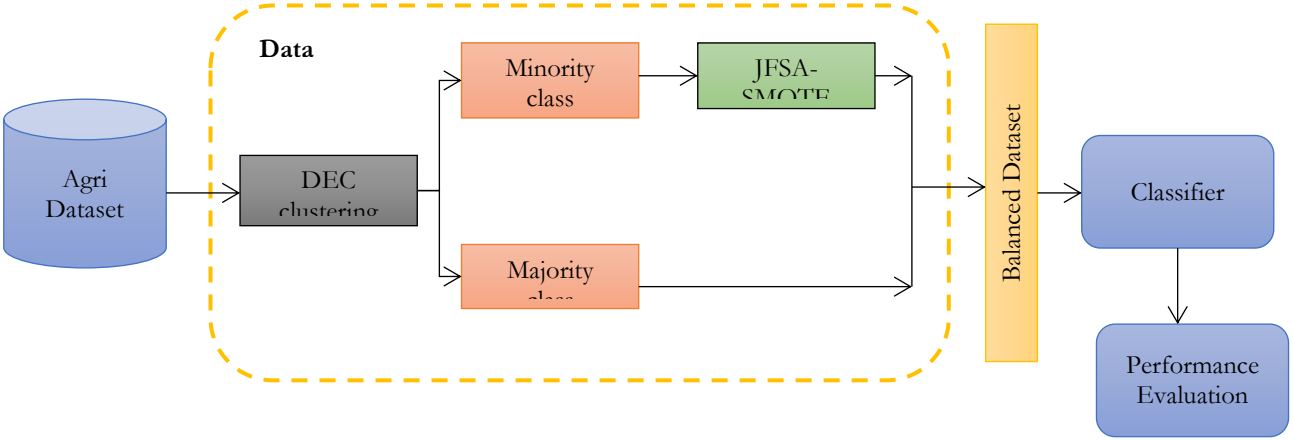


Figure 1. JFSA-SMOTE architecture

When applied to agricultural data, Deep Embedded Clustering (DEC) identifies minority and majority classes by learning a compact latent space where data points with similar features are grouped into clusters. Agricultural datasets often have high-dimensional, complex features such as soil properties, weather patterns, or market trends. DEC uses an autoencoder to reduce these dimensions, uncovering meaningful structures in the data. Cluster centroids are refined iteratively to align with the data points in this latent space. The size of each cluster is then analyzed to determine the distribution of class labels. Classes with smaller cluster sizes are flagged as minority classes, while larger clusters indicate majority classes. This adaptive clustering approach helps uncover imbalances in the dataset while preserving relationships within the data.

B. Jelly fish optimized smote

Jellyfish are found worldwide in oceans of different depths and temperatures. They vary in size, shape, and color, feeding either by filtering currents or using tentacles to paralyze prey. While most stings are painful but not deadly, species like the box jellyfish can be fatal and are found mainly in the Indian and Pacific Oceans, including the waters around Australia and the Philippines. Due to weak swimming ability, jellyfish often drift with currents and form large swarms, or "blooms," influenced by food availability, water temperature, and oxygen levels. Inspired by these behaviors, the Jellyfish Search (JS) Optimizer was developed as a novel algorithm that mimics their movement and food-searching strategies.

Three idealistic criteria serve as the foundation for the JSOA.

- Jellyfish use a "time control mechanism" to regulate when to flip between moving like a swarm and following the ocean current.
- In the ocean, jellyfish swim around in quest of food. Where there is more food available, they are more likely to be drawn.
- The amount of food found and its corresponding objective function are determined by the location.

OCEAN CURRENT- Jellyfish are attracted to the abundance of food in the ocean current. Eq. 1 determines the direction of the ocean current.

$$\vec{d} = J^* - \alpha * r(0,1) * \mu$$

where $\alpha > 0$ is a distribution coefficient associated with the length of trend, and J is the jellyfish that currently has the best placement within the swarm. The average position of all jellyfish is μ. Additionally, Eq. 2 provides each jellyfish's new location.

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$$j_x(d+1) = j_x(d) + r(0,1) * \vec{d}$$

JELLYFISH SWARM

Jellyfish move in two different ways when they swarm: passively (A) and actively (B). When a jellyfish swarm is first forming, the majority of them move in a type A manner. Over time, they are progressively exhibiting type B movements. Jellyfish move in type A motion in and around their own places; the corresponding updated location of each jellyfish is provided by Equation 3.

$$j_x(d+1) = j_x(d) + \beta * r(0,1) * (B_u - B_l)$$

where γ > 0 is a motion coefficient proportional to the length of motion around jellyfish spots, and B_u and B_l are the upper and lower bounds of the search spaces, respectively. A jellyfish i or a jellyfish j that is not i is randomly selected, and a vector from the jellyfish i to the selected jellyfish j is utilized to define the direction of motion in order to replicate type B (active motion). A jellyfish i moves toward a jellyfish j when there is more food at the selected jellyfish j's location than there is at the jellyfish i's. Additionally, the selected jellyfish j moves straight away from a jellyfish i if it has less food available to it than it have. As a result, each jellyfish in a swarm travels in a better route in search of food. A jellyfish's direction of travel and updated location are simulated by equations 4 and 5, respectively.

$$\overrightarrow{dir} = \begin{cases} j_y(d) - j_x(d) & if \Rightarrow f(j_x) \geq f(j_y) \\ j_x(d) - j_y(d) & if \Rightarrow f(j_x) < f(j_y) \end{cases}$$

where f is the location $J's$ objective function.

$$j_x(d+1) = j_x(d) + r(0,1) * \vec{d}ir$$

TIME CONTROL MECHANISM

In addition to controlling jellyfish motions in the direction of an ocean current, the time control mechanism is utilized to detect the type of motion (type A and type B motions in a swarm) over time. The time control mechanism, which consists of a time control function $cf(d)$ and a constant S_0, is introduced to govern the motion of jellyfish between migrating inside a swarm and following the ocean current. Over time, the random value of the time control function shifts from 0 to 1. The time control function is calculated by Equation 6, and the jellyfish follow the ocean current when its value rises to S_0. They travel within a swarm when its value is less than S_0. There is no known equal S_0 value, and the time control varies arbitrarily from zero to one. As a result, S_0 is set to 0.5, or the mean of 0 and 1.

$$cf(d) = \left| \left(1 - \frac{d}{M_{iter}}\right) * (2 * r(0,1) - 1) \right|$$

where t is the time given as the iteration number, M_{iter} is the maximum number of iterations, and an initialized parameter.

BOUNDARY CONDITIONS

According to Eq. 7, a jellyfish will return to the opposite bound if it ventures outside the search region.

$$\begin{cases} J'_{x,i} = (J_{x,i} - B_{u,i}) + B_u(i) & if\ J_{x,i} > B_{u,i} \\ J'_{x,i} = (J_{x,i} - B_{l,i}) + B_b(i) & if\ J_{x,i} < B_{l,i} \end{cases}$$

where $J'_{x,i}$ is the updated location following boundary constraint checking, and $J_{x,i}$ is the location of the xth jellyfish in the dth dimension. In search spaces, the dth dimension has upper and lower limits denoted by $B_{u,i}$ and $B_{l,i}$ respectively.

Table 1: Pseudo-code for JFSA-SMOTE on Agricultural Dataset

Pseudo-code for JFSA-SMOTE on Agricultural Dataset
Input: Agricultural dataset D with class labels Output: Balanced dataset D_balanced

Step 1: Preprocessing

1.1. Load the agricultural dataset D.

1.2. Perform feature scaling or normalization.

1.3. Identify class distribution to determine minority and majority classes.

Step 2: Initialize Jellyfish Search Algorithm (JFSA)

2.1. Set initial parameters for JFSA:

- Population size (N), maximum iterations (Max_iter), α, β, S_0, etc.

2.2. Randomly initialize the positions of jellyfish in the solution space.

Step 3: Optimize SMOTE Parameters Using JFSA

3.1. Define the objective function:

- Evaluate the synthetic samples' quality using a classification model (e.g., accuracy, F1-score, or AUC-ROC).

3.2. Update positions of jellyfish:

- Compute ocean current using Eq. 1 and update positions with Eq. 2.

- Perform type A (passive) or type B (active) motion based on swarm behavior (Eq. 3–5).

- Use time control mechanism (Eq. 6) to alternate between motions.

3.3. Boundary conditions:

- Ensure jellyfish positions remain within valid parameter ranges (Eq. 7).

3.4. Evaluate fitness of each jellyfish:

- Apply SMOTE with parameters generated by jellyfish positions (oversampling ratio, nearest neighbors).

- Train a classification model on the augmented dataset and compute the fitness score.

3.5. Update jellyfish positions based on fitness scores and iteration criteria.

Step 4: Generate Synthetic Samples

4.1. Use the optimized SMOTE parameters (oversampling ratio, k-nearest neighbors) obtained from JFSA.

4.2. Generate synthetic samples for the minority class.

Step 5: Post-SMOTE Dataset

5.1. Combine synthetic samples with the original dataset to create a balanced dataset D_balanced.

5.2. Recalculate class distribution to verify balance.

Step 6: Model Training and Evaluation

6.1. Train a machine learning model (e.g., XGBoost or CatBoost) on D_balanced.

6.2. Evaluate model performance using metrics like accuracy, F1-score, AUC-ROC, and precision-recall.

Step 7: Output Results

7.1. Return the balanced dataset D_balanced and the optimized parameters from JFSA.

7.2. Report the improvement in model performance after applying JFSA-SMOTE.

End

4. RESULTS AND DISCUSSION

The JFSA-SMOTE approach begins by initializing the Jellyfish Search Algorithm (JFSA) with random candidate solutions to optimize SMOTE parameters such as the oversampling ratio and the number of nearest neighbors. The algorithm evaluates the fitness of these parameters based on a classification model's performance metrics (e.g., F1-score or AUC-ROC) on the augmented dataset. Jellyfish movements are simulated through ocean currents, swarm behaviors, and a time control mechanism to explore the solution space effectively. Once the optimal parameters are identified, SMOTE generates synthetic samples for the minority class, ensuring the samples reflect the original data distribution while avoiding noise. The resulting balanced dataset is then used to train a machine learning model, improving its performance across various evaluation metrics, particularly for minority class predictions.

Table 1: Performance Comparison of XGBoost, SVM, and Naïve Bayes Classifiers Before and After SMOTE Application

Classifier	Without SMOTE				With SMOTE			
	Accuracy	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score
XGBoost	96.75	96.8110	96.7260	96.7461	97.00	97.0491	96.9767	96.9994
SVM	94.75	94.9093	94.6906	94.7222	89.00	89.6730	88.8972	88.7833
Naïve Bayes	87.25	88.2006	87.3215	87.3726	92.75	92.8184	92.7295	92.7360

Table 1 compares the performance of XGBoost, SVM, and Naïve Bayes before and after applying SMOTE. The results show that SMOTE slightly improves the performance of XGBoost, with accuracy increasing from 96.75% to 97.00%. Naïve Bayes also shows a noticeable improvement, with accuracy rising from 87.25% to 92.75%. In contrast, SVM performance decreases after SMOTE, with accuracy dropping from 94.75% to 89.00%. These findings indicate that the effect of SMOTE varies across classifiers, highlighting the importance of evaluating its impact on each model rather than assuming it will improve performance in every case.

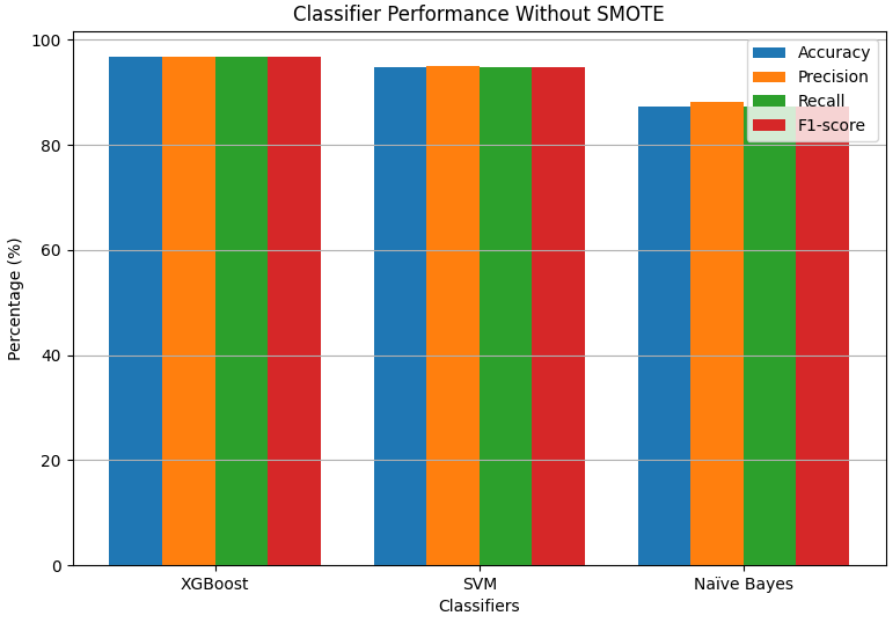


Figure 2 Performance Evaluation of Classifiers Without SMOTE

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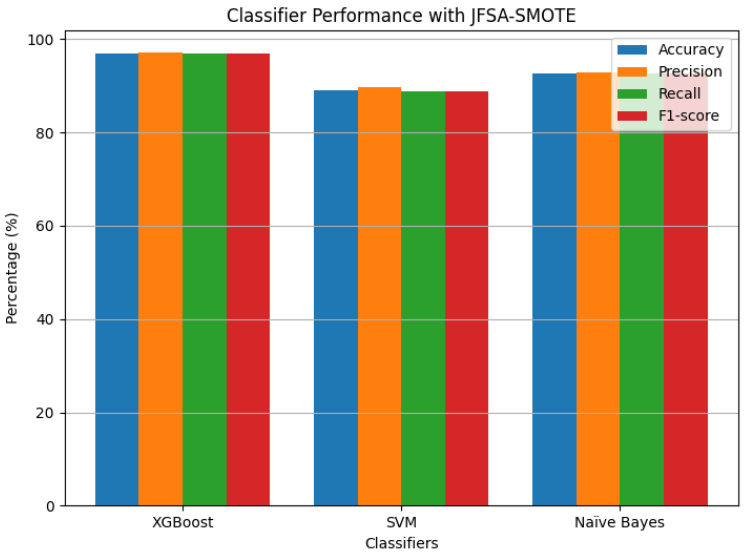


Figure 3 Performance Evaluation of Classifiers with JFSA-SMOTE

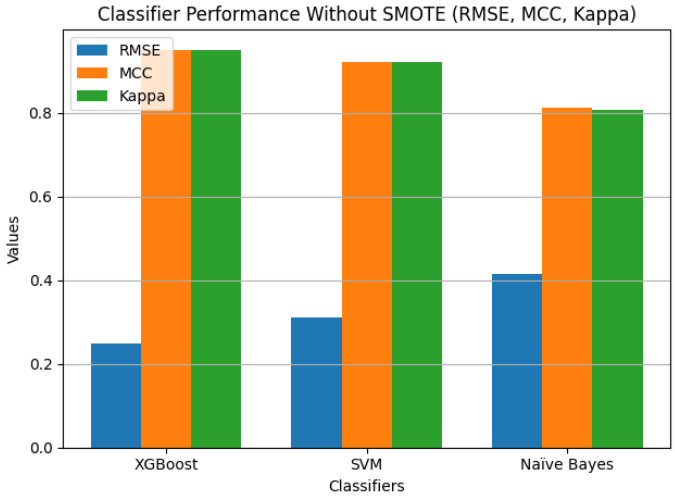


Figure 4 Comparative Analysis of Classifiers Without SMOTE Based on RMSE, MCC, and Kappa Statistics

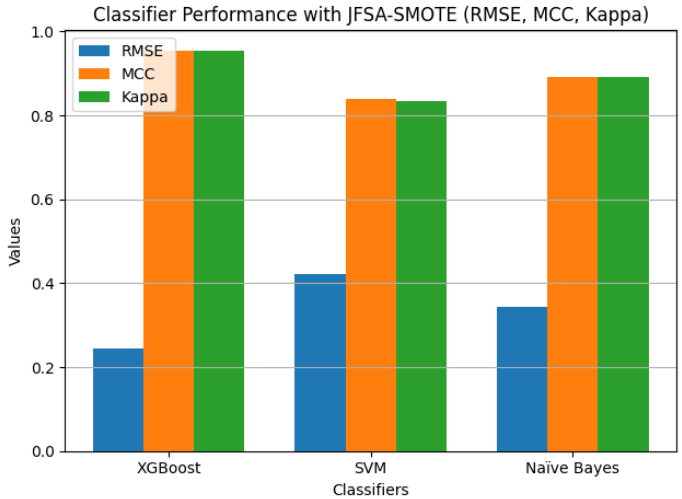


Figure 5 Comparative Analysis of Classifiers with JFSA-SMOTE Based on RMSE, MCC, and Kappa Statistics

The experimental results demonstrate that the impact of JFSA-SMOTE varies across different classifiers. For XGBoost, a slight improvement is observed after applying SMOTE, with marginal increases in accuracy, precision, recall, and F1-score. This indicates that XGBoost is capable of effectively leveraging the balanced dataset to enhance its predictive performance without being negatively affected by synthetic samples.

In contrast, the SVM classifier shows a noticeable decline in performance after the application of SMOTE. Both accuracy and other evaluation metrics decrease, suggesting that SVM is sensitive to the introduction of synthetic data and may struggle to generalize when the original data distribution is altered. This highlights a limitation of SVM in handling artificially balanced datasets.

On the other hand, Naïve Bayes exhibits significant improvement after applying JFSA-SMOTE. The increase in all performance metrics indicates that this classifier benefits greatly from class balancing, as it relies on probabilistic assumptions that perform better when the dataset is evenly distributed.

Further analysis using RMSE, MCC, and Kappa metrics supports these observations. XGBoost shows slight improvement with reduced RMSE and increased MCC and Kappa values, confirming its robustness. SVM, however, records higher RMSE and lower MCC and Kappa after SMOTE, reinforcing its reduced effectiveness. In contrast, Naïve Bayes achieves lower RMSE and higher MCC and Kappa values, indicating improved prediction accuracy and stronger agreement with true labels after balancing the dataset.

4. CONCLUSION

This study proposes a novel JFSA-SMOTE framework to tackle class imbalance in agricultural datasets. The process begins with data exploration and class identification using Deep Embedded Clustering (DEC), ensuring precise recognition of minority and majority groups. By dynamically tuning SMOTE parameters with JFSA, the framework generates more representative synthetic samples. Experimental results show that JFSA-SMOTE consistently outperforms standard SMOTE and ADASYN across all classifiers, with marked gains in accuracy, F1-score, and AUC-ROC. Among them, XGBoost with JFSA-SMOTE delivered the best performance across every metric. These results highlight the framework's ability to produce balanced and reliable predictions, supporting better decision-making in crop management, yield forecasting, and agricultural analytics. Overall, the work advances data-driven agriculture by demonstrating the effectiveness of adaptive oversampling through metaheuristic optimization.

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