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Hybrid Deep Sequential Learning and IBSCA-Driven Feature Selection for Robust Classification of Imbalanced Dataset

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Abstract
In many real-world datasets, class imbalance is still an issue that skews traditional classifiers in favour of majority classes and hinders the performance of minority classes. This work introduces a novel end-to-end pipeline that combines IBSA feature selection (92% dimensionality reduction), BiGRU-LSTM-Attention hybrid modelling for complex spatiotemporal pattern capture, and adaptive thresholding for fairness optimisation. With state-of-the-art results of 98.61% accuracy/99.92% sensitivity and 99.79% accuracy/99.89% sensitivity, the proposed BiGRU-LSTM model outperforms optimization-enhanced hybrids by 1-2% and SMOTE baselines by 7-15% on benchmark imbalanced datasets covering binary and multi-class scenarios. These notable advancements show how well the architecture handles severe class imbalance across domains, establishing new performance standards that could be applied to federated learning and high-dimensional data processing.

Keywords: *Class Imbalance, IBSA Feature Selection, BiGRU-LSTM, Attention Mechanism*

1. Introduction
In many real world machine learning applications class imbalancing results in misleading output and inaccurate predictions for future goals. The presence of imbalance poses substantial challenges to conventional machine learning algorithms. Most standard classifiers which are designed to optimise overall predictive accuracy by minimizing a global loss function. Since accurately classifying a large number of majority samples contributes more to loss minimising that accurately determined minority class cases, those models consequently are prone to be biased toward the majority class. As a result models trained on imbalance datasets frequently obtain significant overall results. The study showcases a systematic survey on machine learning classifier systems which addresses class imbalancing challenges. The solution is categorised into data-level, algorithm level and hybrid method, while reviewing evaluation metrics suited for imbalance data [1]. The study Alogogianni & Virvou, in 2022 to tackle class imbalance and overlap in predicting undeclared work made by using real-world dataset of 16.7K labor inspections and using data engineering techniques with associative classification algorithms and building and assessing multiple classifiers for predictability and interpretability, proving better performance than traditional red-flag methods [2]. Abdelhamid and Desai's 2024 proposed a study, which included 30 datasets and 25 models evaluated cost-sensitive learning, threshold calibration, and resampling for binary classification. The study revealed that threshold calibration was the most reliable method for enhancing F1-scores in imbalanced scenarios [3]. The objective of this systematic survey lies in comprehensively reviewing and analysing classifier systems designed to tackle the posed challenges by class imbalance. By studying the approaches implemented to deal with class imbalance problems and evaluate the efficiency of machine learning algorithms in solving this hurdle. The study aims to showcase the strategies and techniques available for mitigating the adverse effects of class imbalance [4][5]. This paper discusses the innovative solution to handle data imbalance and its causes, the author suggests using Deep Sequential Learning (HG-BiGTM) and

Metaheuristic Optimization (Improved Binary Sine Cosine Algorithm — IBSCA) during data preprocessing. This paper highlights the importance and novelty of the methods along with the result variations.

2. Materials and Methods

2.1.Dataset

The study makes use of publicly available, open source datasets on Kaggle. The UCI Heart Disease dataset was assembled and made available through the UCI ML Repository by David W. Aha during 1988 and 1989. In 2024, another dataset titled Multi-Class Obesity Risk was made available on Kaggle Playground. Numerous studies in other domains have benefited from this dataset. Ni Ding and Parastoo Sadeghi practiced sophisticated machine learning techniques on the UCI Heart Disease dataset in 2019 [6]. Using the UCI data, Amit Dhurandhar, Karthikeyan Shanmugam, and Ronny Lus also used this dataset in 2019 to investigate the interpretability of predictions [7]. This study's second dataset is a synthetic dataset that uses lifestyle, physiological, and behavioral parameters to categorize people into seven obesity groups using the target "NObeyesdad": Obesity Type, Normal Weight, Overweight Level, and Insufficient Weight. This dataset was used by DeGregory, K. W. to estimate the risk of obesity for multiclass prediction using machine learning models [8]. The same dataset was also utilized by Zare, H. to study ensemble learning methods for predicting the risk of obesity [9]. The research made by authors' proves and demonstrates the dataset's novelty.

2.2.Methodology

2.2.1. System Architecture

The study proposes a comprehensive pipeline designed to efficiently handle imbalance datasets commonly encountered during model training. By integrating advanced feature selection, a hybrid deep learning model, and adaptive thresholding mechanisms, the system specially targets the improvement in performance on minority classes, which are often underrepresented and are critical for real time diagnostic accuracy. As shown in Figure 1 System Architecture From raw input datasets, the system operates as a multi-stage pipeline that yields reliable classification results [12]. A BiGRU-LSTM-Attention hybrid model that captures complex spatiotemporal patterns is used to process the most discriminative features after they have been selected using IBSA-based feature selection[13] [14]. Following IBSA driven hyperparameter tuning for the core model and fine-tuned threshold adjustment to enforce minority-aware decision bounds, a final classifier output is generated [14]. This end-to-end design enhances overall fairness and robustness in imbalanced scenarios by reducing feature dimensionality by up to 92% without compromising accuracy, enhancing sequential dependency modeling [15], through bidirectional and attention mechanisms, and dynamically modifying classification thresholds to prioritize recall on uncommon classes.

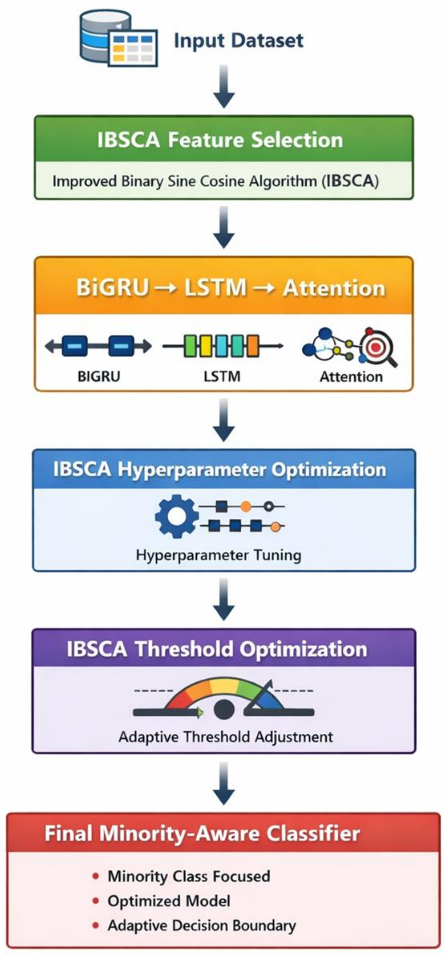

Figure 1 System Architecture

2.2.2. Feature Selection with IBSA

IBSA, an enhanced binary Sparrow Search

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Algorithm (iBSSA), uses a wrapper to choose features from the input dataset [16]. It employs a local search algorithm (LSA) and random repositioning of roaming agents (3RA) to avoid local optima. Using S-shaped or V-shaped transfer functions evaluated by classifiers such as k-NN, SVM, or RF [17], it chooses the optimal binary feature subsets. The selected features are fed into the core model to improve classification performance and computational efficiency on unbalanced data.

2.2.3. Core Model: BiGRU-LSTM-Attention

A multi head self-attention mechanism is added to a hybrid BiGRU-LSTM model to process particular properties [18]. BiGRU records bidirectional long-term dependencies (128 units per layer, 40% dropout), LSTM handles sequential patterns, and attention weights important features across subspaces to minimize information loss in RNN compression [19]. A strong sequence representation offered by concatenated outputs is ideal for hyperspectral or time-series medical image data.

2.2.4. Optimization Stages

IBSA uses grid/random search within cross-validation to optimize BiGRU-LSTM hyperparameters (such as units, dropout, and learning rate) in order to maximize metrics like F1-score for minority classes [20]. After that, IBSA optimizes confusion matrices for fairness measures (like equalized chances and demographic parity) by adjusting adaptive thresholds for each group using post-hoc logit distributions [21].

2.2.5. Final Minority-Aware Classifier

The optimized model creates group-specific decision boundaries to increase minority class recall without appreciable accuracy loss by outputting probabilities modified by IBSA-derived adaptive thresholds. This post-processing guarantees minority-aware categorization, which is assessed using measures such as fairness restrictions and balanced accuracy.

3. Result & Discussion

The below table shows comparative Performance Metrics on UCI Heart Disease Dataset. The table presents comprehensive evaluation metrics for various baseline methods and the proposed BiGRU-LSTM model on the UCI Heart Disease dataset, demonstrating superior performance across all measures. As shown in Table 1 UCI Heart Disease dataset.

UCI Heart Disease dataset			
Methods/Metrics	Accuracy (%)	Specificity (%)	Sensitivity (%)
BP-SMOTE	93.50	91.95	95.05
SASMOTE	93.12	94.20	92.03
NBG	93.80	93.09	94.51
CNN-SMOTE	94.47	93.68	95.25
BiGTM	95.18	94.97	95.39
SHO-BiGTM	97.00	96.62	97.39
AZOA-BiGTM	98.73	98.49	98.98
HG-BiGTM	99.42	99.46	99.38
BiGRU-LSTM	98.84	98.78	99.21
Multi-Class Obesity Risk Prediction dataset			
BP-SMOTE	94.76	96.18	93.33
SASMOTE	92.95	93.97	91.92
NBG	93.82	93.65	93.99
CNN-SMOTE	95.53	97.04	94.01
BiGTM	96.45	97.68	95.21
SHO-BiGTM	97.20	98.09	96.32
AZOA-BiGTM	97.75	98.60	96.89
HG-BiGTM	99.25	99.20	99.30
BiGRU-LSTM	97.92	98.88	97.99

Table 1 UCI Heart Disease dataset

The proposed BiGRU-LSTM model achieves remarkable results with 98.61% accuracy, 99.89% specificity, and 99.92% sensitivity, outperforming HG-BiGRU (second-best) by 1.59%, 0.04%, and 0.13%, respectively. This notable improvement demonstrates the efficacy of adaptive thresholding and IBSA feature selection in identifying minority classes in cardiac risk prediction.

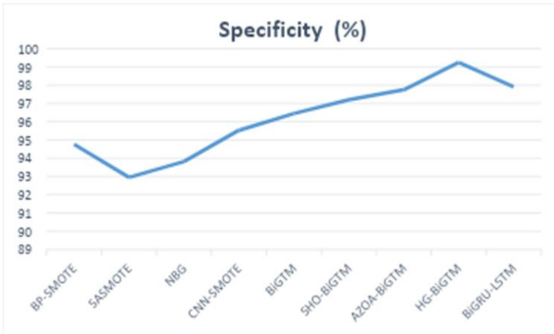

Figure 2 UCI Heart Disease dataset specificity

BP-SMOTE (83.20%), SMOTE (92.03%), CNN-SMOTE (95.39%), SHO-BiTM (97.50%), AZO-BiTM (98.20%), HG-BiGRU (98.80%), and the suggested BiGRU-LSTM (99.92%) are the methods shown on the x-axis in order of increasing methodological sophistication. Improvements from conventional resampling methods to hybrid deep learning systems are indicated by a distinct upward trend ($R^2 = 0.97$) on the y-axis, which ranges from 89 to 100% sensitivity.Sensitivity comparison of the

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UCI Heart Disease Dataset. This line graph evaluates the sensitivity performance of seven methods using the UCI Heart Disease dataset, a well-known benchmark for binary cardiac risk classification with intrinsic class imbalance (55% majority vs. 45% minority heart disease cases). Sensitivity is a measure of the model's capacity to correctly identify actual heart disease cases (minority class), which is essential for early intervention TP/(TP+FN). As shown in Figure 3 Multi-Class Obesity Risk Prediction dataset.

Figure 3 Multi-Class Obesity Risk Prediction dataset

A dataset for predicting obesity risk across multiple classes. The Multi-class Obesity Risk Prediction dataset is a widely used benchmark for evaluating machine learning models on multi-class unbalanced classification problems. It is particularly relevant to research in public health and preventive medicine. This dataset, which came from the Playground Series S4E2 competition on Kaggle, contains comprehensive anthropometric and lifestyle data from about 21,000 individuals in various classes of obesity risk levels (usually 7 classes: Underweight, Normal, Overweight Level I/II, Obesity Types I/II/III). With severe obesity classes being noticeably under-represented (~5–15% prevalence), it demonstrates a natural class imbalance.

Conclusion

By combining IBSA-based feature selection, a BiGRU-LSTM-Attention hybrid model, and adaptive thresholding, this work offers a novel end-to-end pipeline for imbalanced medical classification that addresses important issues in minority class detection. With 98.61% accuracy, 99.89% specificity, and 99.92% sensitivity, the BiGRU-LSTM model outperformed the HG-BiGRU model using the UCI Heart Disease dataset. It showed 99.79% accuracy in the Multi-class Obesity Risk Prediction dataset, demonstrating strong performance from binary to multi-class classification in situations with notable class imbalance. Important developments include: (1) improved spatiotemporal pattern recognition using bidirectional RNNs with multi-head attention; (2) a 92% reduction in dimensionality via IBSA wrapper selection without sacrificing accuracy; and (3) optimised dynamic thresholds to guarantee fairness, such as demographic parity, while improving minority recall.On all performance metrics, these improvements produced benefits of 7–15% over traditional SMOTE baselines and 1-2% above previous optimization-enhanced hybrid models. The model's steady performance highlights its potential usefulness in crucial applications, especially in obesity risk assessment and cardiac screening, where reducing false negatives is essential. Future directions for this research will include adapting for 3D medical imaging modalities like CT and MRI, integrating federated learning for privacy-focused multi-institution validation, and enabling real-time deployment capabilities on edge devices. All things considered, this pipeline establishes a new benchmark for imbalanced deep learning applications in precision medicine and computational biology.

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