

A Fibonacci-Based Dynamic Neural Network Architecture for Imbalanced Classification of Higher Education Performance

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Abstract

This study aims to address two problems in neural network design: the lack of a principled method for choosing hidden-layer neuron counts, and the reliability loss caused by severe class imbalance. To meet this objective, the study propose the Fibonacci Dynamic Neural Network, contributing, to our knowledge, the first architecture unifying number-theoretic hidden-layer sizing with imbalanced-learning correction, an unbiased selection property proven formally, and cross-domain validation. Conceptually, candidate hidden-layer widths are generated from the Fibonacci sequence: because consecutive terms grow proportionally toward the Golden Ratio, the resulting set spans a non-redundant, well-distributed range of capacities, unlike arbitrary sets from conventional methods. One candidate is drawn per layer via a discrete uniform distribution, giving every option equal selection probability, while class imbalance is corrected through synthetic minority oversampling applied only to training data. The architecture was evaluated experimentally on three benchmark datasets spanning higher education, credit card fraud, and charitable donation prediction, with imbalance ratios from about eighteen-to-one to nearly five hundred eighty-to-one, tested across five seeds against five baselines and an ablation study via the Wilcoxon signed-rank test. It achieved macro F1-scores of approximately 0.83, 0.94, and 0.81, improvements of sixteen, five, and sixteen percent over the strongest baseline, with the smallest training-test performance gap of any model tested; oversampling and Fibonacci spacing contributed most to these gains. These findings suggest number-theoretic structures offer a practical, reproducible basis for architecture design under class imbalance, useful for future work on automated range selection and for deploying reliable classifiers in imbalanced real-world settings.

Keywords: Fibonacci Sequence, Dynamic Neural Network, Imbalanced Classification, Discrete Uniform Distribution, SMOTE, Hidden Layer Optimization, Artificial Neural Network, Multi-Class Classification

1. Introduction

Determining the optimal number of neurons in hidden layers of an artificial neural network (ANN) is one of the most consequential yet least systematically addressed architectural design decisions. Current practice overwhelmingly relies on trial-and-error, empirical heuristics such as $n = \sqrt{n_{in} \times n_{out}}$, or computationally expensive metaheuristics. None of these provides a mathematically structured, reproducible, and bias-free framework for exploring the architecture search space [1], [2], [3], [4].

Simultaneously, class imbalance poses a pervasive challenge in real-world classification. When class label distributions are highly skewed, conventional ANNs develop systematic bias toward the majority class, achieving superficially high accuracy while failing to identify critical minority classes [5]. This failure is especially severe in higher education performance evaluation, financial fraud detection, and medical diagnosis such as domains where minority classes carry the highest practical importance [6], [7]. In Indonesia, the SINTA (Science and Technology Index) portal, the national platform for evaluating research and institutional performance, classifies 2,580 universities across five performance clusters (Mandiri: 51, Utama: 216, Madya: 294, Pratama: 554, Binaan: 1,465), yielding an Imbalance Ratio of 28.72:1.

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Dynamic neural network architectures, as opposed to static or heuristic classifiers, remain unexplored for this severely imbalanced institutional-performance classification domain such as a gap this paper directly addresses.

This paper presents the Fibonacci Dynamic Neural Network (FDNN), addressing both challenges simultaneously through: (1) the Fibonacci sequence as a structured mathematical basis defining candidate neuron counts; (2) the Discrete Uniform Distribution as a bias-free exploration mechanism; and (3) SMOTE for class rebalancing. Contributions: (i) formalization of FDNN with mathematical proofs of its bias-free properties; (ii) complete algorithmic specification; (iii) comprehensive empirical evaluation on three benchmark datasets; and (iv) ablation study quantifying each component's individual contribution.

2. Literature Review

2.1. ANN Architecture Optimization

Determining optimal neuron counts has been studied for decades without a universal solution. Abdolrasol et al. [1] review ANN optimization approaches and find that genetic algorithm-based methods, while effective, incur prohibitive computational costs that limit practical applicability. Moshkbar-Bakhshayesh [2] demonstrates optimal feed-forward architecture identification using GA combined with LM and BR algorithms, but the approach is domain-specific and not generalizable. Adil et al. [4] study the effect of neuron count and layer depth on ANN performance, confirming that no systematic mathematical basis exists for neuron count selection. Ali et al. [8] compare ANN architectures for solar radiation prediction, demonstrating that structured architecture search consistently outperforms trial-and-error approaches.

Yotov and Hadzhikolev [3] derive mathematical upper bounds for neuron counts using deterministic formulas, producing a single fixed value rather than an explorable candidate distribution, the fundamental limitation FDNN directly addresses. Alzubaidi et al. [9] confirm in a comprehensive deep learning review that architectural design remains largely empirical despite decades of research. Taye [10] further explores deep learning architectures and workflows, noting that hidden layer configuration remains an open problem. Lee et al. [11] apply ANNs to landslide susceptibility modelling and confirm that neuron count selection significantly impacts model performance, yet no principled approach exists.

2.2. Dynamic Neural Networks

Han et al. [12] survey dynamic neural networks in a comprehensive IEEE TPAMI paper and demonstrate that adaptive architectures consistently outperform static counterparts. Critically, they identify the absence of a structured mathematical basis for neuron count determination as a key research gap (precisely the gap FDNN fills). Verma et al. [13] trace neural network developments from static to dynamic models and confirm that no existing approach integrates number theory as the mathematical basis for dynamic architecture search. Ma and Tang [14] analyze neuronal dynamics and computational implications, highlighting the adaptability benefits of dynamic architectures.

2.3. Imbalanced Classification

Chawla et al. [5] introduced SMOTE (Synthetic Minority Over-sampling Technique), generating synthetic minority samples through linear interpolation $x_{syn} = x_i + \lambda(x_{nn} - x_i)$, where $\lambda \in U(0,1)$. SMOTE has since become the foundational technique for imbalanced classification and has been validated across diverse domains [6], [7]. Hattiya et al. [15] apply CNN architectures to diabetic retinopathy detection and demonstrate the critical role of class imbalance handling in medical imaging. Chen et al. [7] demonstrate AI-based image recognition and confirm that imbalanced datasets are among the most significant performance barriers. Saberi-Movahed et al. [16] propose hybrid approaches for water quality prediction and confirm SMOTE effectiveness for environmental classification tasks with severe class imbalance.

2.4. Fibonacci Sequence in Computing

Oduol and Okoth [17] provide rigorous mathematical treatment of generalized Fibonacci numbers and their convergence properties toward the Golden Ratio. Somprom et al. [18] analyze alternating sums of Fibonacci and Lucas numbers, providing theoretical foundations for Fibonacci-based computational approaches. Mougkogiannis and Adamatzky [19] demonstrate Fibonacci sequence applications in computational systems, specifically showing how

Fibonacci structures emerge in complex adaptive systems. Yang and Wang [20] provide a neuroscientist primer on ANNs, emphasizing the importance of principled mathematical design in neural network architectures.

2.5. Research Gap

The reviewed literature reveals three interconnected gaps motivating FDNN. First, no existing approach provides a mathematically structured, bias-free, computationally efficient method for determining neuron counts in ANN hidden layers simultaneously. Methods such as Bayesian optimization [21] and Hyperband [22] perform structured architecture search but treat neuron count as a general hyperparameter without imposing a principled mathematical growth structure, and they incur substantial overhead (Bayesian optimization: $O(T^3)$ per update from Gaussian Process inference; Hyperband: repeated partial training across successive halving brackets). Neural Architecture Search frameworks typically target macro-level topology rather than the specific hidden-layer neuron count problem. Random Search applies equal probability over continuous or arbitrary discrete ranges without the proportional spacing that Fibonacci provides. FDNN differs from all these by restricting the search space to a number-theoretically structured set where spacing grows proportionally toward the Golden Ratio, ensuring genuinely diverse capacity levels without redundancy. Second, dynamic architecture search and imbalanced data handling have not been unified in a single coherent framework applicable across multiple domains. Third, dynamic neural network application to higher education performance classification via SINTA data remains unexplored. FDNN is specifically designed to close all three gaps simultaneously, while acknowledging that the mathematical claims are grounded in the structural properties of Fibonacci spacing rather than formal optimality proofs.

3. Methodology

3.1. Proposed FDNN Architecture

FDNN integrates two complementary mathematical pillars. The first pillar is the Fibonacci sequence [17], defined by:

$$F(0) = 0, \quad F(1) = 1, \quad F(n) = F(n-1) + F(n-2), \quad n \geq 2. \quad (1)$$

The ratio between consecutive terms converges to the Golden Ratio $\phi = (1+\sqrt{5})/2 \approx 1.618$ [19], ensuring proportional, hierarchical capacity growth. This property is mathematically proven: $\lim_{n \rightarrow \infty} \frac{F(n+1)}{F(n)} = \phi$. The candidate neuron set S_F for designer-specified range $[a, b]$ is:

$$S_F = \{F(k) \mid a \leq F(k) \leq b, k \in \mathbb{N}_0\}. \quad (2)$$

Example: $[a, b] = [5, 55] \rightarrow S_F = \{5, 8, 13, 21, 34, 55\}$, $|S_F| = 6$. The second pillar is the Discrete Uniform Distribution for bias-free neuron selection per hidden layer l [12]:

$$n_l \sim U_{\text{disc}}(S_F), \quad P(n_l = F(k)) = \frac{1}{|S_F|}, \quad \forall F(k) \in S_F. \quad (3)$$

Layers are sampled independently, so $n_1, \dots, n_{L-1}$ are i.i.d. random variables. This guarantees exploration without apriori bias, grounded in Laplace's principle of indifference. Forward propagation equations are [20], [23]:

$$h^{(l)} = \text{ReLU}(W^{(l)}h^{(l-1)} + b^{(l)}), \quad l = 1, \dots, L-1 \quad (4)$$

$$\hat{y} = \text{Softmax}(W^{(L)}h^{(L-1)} + b^{(L)}). \quad (5)$$

Weights use Xavier/Glorot Initialization [24] to prevent vanishing/exploding gradients:

$$W_{ij}^{(l)} \sim U\left(-\sqrt{\frac{6}{n_{l-1}+n_l}}, \sqrt{\frac{6}{n_{l-1}+n_l}}\right). \quad (6)$$

Figure 1 illustrates the proposed FDNN architecture, consisting of an input layer, dynamically configured hidden layers, and a Softmax output layer. At each iteration, the number of neurons in each hidden layer, n_l , is independently sampled from the Fibonacci-based candidate set S_F using a discrete uniform distribution. Thus, each candidate neuron count has an equal selection probability of $P(n_l = F(k)) = 1/|S_F|$. The output layer uses the Softmax activation function to generate probabilities for C target classes. Figure 2 shows the complete nine-step implementation pipeline of the

proposed FDNN framework: raw data acquisition → missing-value imputation → label encoding → Min–Max scaling → recursive feature elimination (RFE) → stratified train–test splitting → SMOTE combined with undersampling on the training set → FDNN training with dynamic hidden-layer configuration → model evaluation.

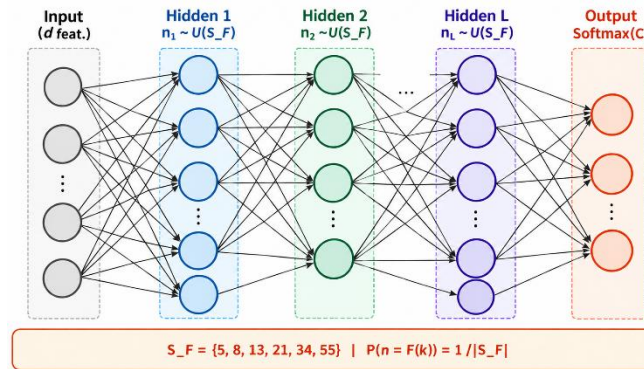


Figure 1. Proposed FDNN architecture

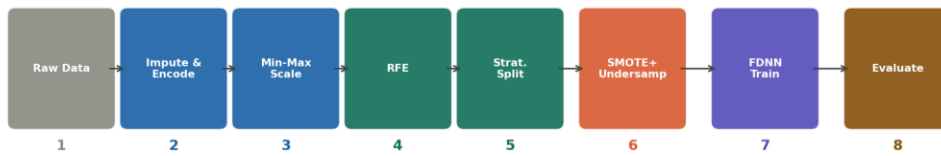


Figure 2. FDNN nine-step implementation pipeline

3.2. Mathematical Proofs

Proposition 1 Equal-Probability Sampling within S_F : Under $U_{\text{disc}}(S_F)$, each candidate $F(k) \in S_F$ has an equal selection probability of $P(n_l = F(k)) = 1/|S_F|$, as defined by the discrete uniform distribution. Thus, every candidate in S_F has the same marginal probability of being selected before its performance is observed. The term *bias-free* is used here in a specific and restricted sense: given the selected interval $[a, b]$ and the Fibonacci membership criterion, no candidate within S_F is assigned a higher a priori selection probability than another. This property concerns only the sampling distribution within the predefined candidate set and does not imply optimality or convergence guarantees for the overall architecture search process.

The interval $[a, b]$ itself introduces an inductive bias during the candidate-set definition stage, which is distinct from the within-set sampling bias considered here. Furthermore, independent and identically distributed sampling across hidden layers, $n_1, \dots, n_{L-1}$, ensures that the joint configuration space can be explored without inter-layer dependency. Formally, for any two distinct configurations $c_1 = (n_1^{(1)}, \dots, n_{L-1}^{(1)})$ and $c_2 = (n_1^{(2)}, \dots, n_{L-1}^{(2)})$ in S_F^{L-1} , their selection probabilities are identical: $P(\text{configuration} = c_1) = P(\text{configuration} = c_2) = \left(\frac{1}{|S_F|}\right)^{L-1}$. This equal-probability property defines the notion of *bias-free sampling within the specified search space*.

Proposition 2 Proportional Capacity Growth: For two consecutive Fibonacci elements $F(k)$ and $F(k+1)$ in S_F , their ratio approaches the Golden Ratio, $\lim_{k \rightarrow \infty} \frac{F(k+1)}{F(k)} = \varphi \approx 1.618$. Consequently, Fibonacci-based neuron counts exhibit approximately geometric spacing with a growth factor of 1.618. This provides a relative scaling between adjacent configurations that differs from both linear and conventional geometric spacing. For comparison, six linearly spaced integers within $[5, 55]$, such as 5, 15, 25, 35, 45, 55, have constant absolute differences but progressively smaller relative ratios as the neuron count increases. For example, $\frac{15}{5} = 3.0$, $\frac{25}{15} \approx 1.67$, $\frac{35}{25} = 1.40$. This pattern results in increasingly dense relative spacing among larger configurations. In contrast, geometric spacing with a base of 2 produces substantially larger capacity increments. For example, the sequence 5, 10, 20, 40 contains only four values before exceeding 55, potentially leaving intermediate capacity levels unrepresented.

Fibonacci spacing, with an asymptotic ratio of approximately 1.618, provides an intermediate scaling between the relative redundancy of linear spacing and the larger capacity jumps of geometric spacing. It therefore offers a mathematically motivated mechanism for maintaining relatively consistent growth between consecutive candidate capacities. However, this argument is structural rather than a formal proof of optimality. The proposed Fibonacci spacing is presented as a principled design choice whose mathematical properties distinguish it from simpler spacing strategies. A systematic evaluation of alternative spacing strategies across diverse problem domains remains an opportunity for future research.

3.3. FDNN Iterative Algorithm

The FDNN iterative search process (algorithm 1) samples a new architecture from S_F via Discrete Uniform Distribution at each iteration, trains with Adam optimizer [25] and Dropout regularization, evaluates using F1-macro, and retains the best configuration. Training uses Categorical Cross-Entropy loss and early stopping (patience=15) to prevent overfitting.

Algorithm 1. FDNN Iterative Algorithm Specification

Input: $D_{train}, D_{val}, [a,b], L, T_{max}, \tau$
Output: θ^* (best model parameters)
Generate $S_F = \{F(k) \mid a \leq F(k) \leq b\}$ [Eq. 2]
Apply SMOTE + Random Undersampling exclusively on D_{train}
Initialize: $\theta^* \leftarrow \emptyset, Score^* \leftarrow -\infty$
FOR $t = 1$ TO T_{max} DO
 FOR $l = 1$ TO $L-1$: $n_l \sim U_{disc}(S_F)$ [Eq. 3]
 Build FDNN($d, [n_1, \dots, n_{L-1}], C$); Xavier Initialization [Eq. 6]
 Train: $\theta(t) \leftarrow \operatorname{argmin}_{\theta} \{-(1/N) \sum y_{ic} \log \hat{y}_{ic}\}$ [Adam]
 Score(t) $\leftarrow$ F1-macro($\theta(t), D_{val}$)
 IF Score(t) > Score*: $\theta^* \leftarrow \theta(t); Score^* \leftarrow$ Score(t)
 1 IF Score* $\geq \tau$: BREAK {optional early termination}
END FOR
RETURN θ^*

3.4. Dataset

Three datasets with distinct imbalance characteristics were used (table 1). SINTA 2024 was collected via automated web scraping using Python Requests and BeautifulSoup from the official SINTA portal and contains quantitative Tridharma performance indicators. Credit Card Fraud [5] contains 284,807 European cardholder transactions with PCA-anonymized features V1–V28. KDD Cup 1999 contains demographic and donation history variables with binary target TARGET_B. Figure 3 visualizes the severe class imbalance confirming the necessity of SMOTE.

Table 1. Benchmark Dataset Characteristics

Dataset	Samples	Features	Classes	IR	Class Labels
SINTA 2024	2,580	67	5	28.72:1	Mandiri, Utama, Madya, Pratama, Binaan
Credit Card Fraud	284,807	30	2	577.88:1	Normal (0), Fraud (1)
KDD Cup 1999	5,000*	481	2	17.66:1	Non-Donor (0), Donor (1)

*Representative sample. $IR = n_{majority} / n_{minority}$. All exceed $IR=10$ (severe imbalance threshold).

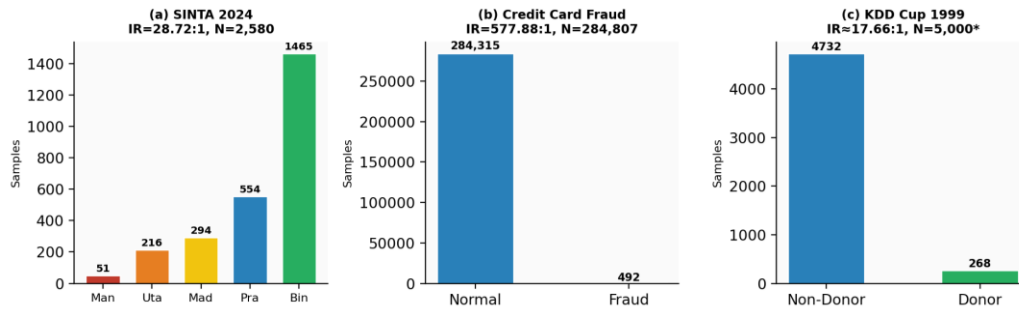


Figure 3. Class distribution of three benchmark datasets. (a) SINTA 2024: Binaan (1,465) vs Mandiri (51), $IR=28.72:1$. (b) Credit Card Fraud: Normal (284,315) vs Fraud (492), $IR=577.88:1$ — the most extreme. (c) KDD Cup 1999: Non-Donor (4,732) vs Donor (268), $IR\approx 17.66:1$.

3.5. Preprocessing Pipeline

A standardized six-step pipeline was applied to all datasets: (1) Missing value imputation using column mean $\hat{x}_{ij} = (1/|S_j|)\sum x_{kj}$ (SINTA: 666 missing values = 0.54%); (2) Label encoding; (3) Min-Max scaling $x'_{ij} = (x_{ij} - \min_j) / (\max_j - \min_j)$ applied exclusively on training data; (4) Recursive Feature Elimination (RFE) with Random Forest estimator [1] (SINTA: 67→32 features; KDD Cup: 481→50); (5) Stratified split 80%/20% preserving class proportions; (6) SMOTE + Random Undersampling [5] applied exclusively on training data to prevent data leakage.

3.6. Experimental Scenarios and Baselines

Three Fibonacci range scenarios were evaluated: $S1: [5,55] \rightarrow S_F = 5,8,13,21,34,55, E[n_i] = 22.67$; $S2: [8,89] \rightarrow S_F = 8,13,21,34,55,89, E[n_i] = 36.67$; $S3: [13,144] \rightarrow S_F = 13,21,34,55,89,144, E[n_i] = 59.33$. All use $T_{\max} = 50$ and $|S_F| = 6$. The three ranges were chosen to represent low, medium, and high capacity regimes relative to the input dimensionality of each dataset (32 features after Recursive Feature Elimination for SINTA; 30 for Credit Card Fraud; 50 for KDD Cup). The lower bound $a = 5$ was set to ensure sufficient representational capacity above a trivially small width; the upper bounds b were set so that the largest configuration remains computationally tractable and does not exceed approximately four times the input dimension (a commonly applied heuristic ceiling for feedforward network width). The study acknowledges this selection is partially heuristic; automated range determination based on dataset intrinsic dimensionality is identified as future work. Computational cost: iterative training of $T_{\max} = 50$ architectures imposes cost proportional to 50 single ANN training runs. On the experimental hardware, total FDNN training on SINTA required approximately 20-26 minutes across 50 iterations (26 minutes for the widest Scenario 3), compared to approximately 33 hours estimated for a Genetic Algorithm with population 100 over 50 generations — a reduction factor of approximately 76-99 times. Credit Card Fraud required approximately 154 minutes total due to the large sample count. These figures confirm that FDNN's computational overhead relative to a single static ANN is bounded and practically acceptable for the study settings.

Five baseline models were evaluated under identical preprocessing and evaluation conditions: (1) Static ANN (fixed 64 neurons per layer determined through trial-and-error); (2) Heuristic ANN (neuron count $n = \text{floor}(\sqrt{n_{\text{in}} \times n_{\text{out}}})$ per standard empirical rule [1]; (3) RF-NN (Fibonacci candidates with weighted non-uniform selection, designed to isolate the specific contribution of the Discrete Uniform Distribution over general Fibonacci-based search); (4) XGBoost with `scale_pos_weight` set to the inverse class frequency ratio (a strong gradient boosting baseline widely used in imbalanced classification benchmarks); (5) Focal Loss ANN (a neural network identical in depth and preprocessing to the Static ANN but trained with focal loss ($\gamma = 2.0$) targeting minority class improvement through down-weighting of easy majority samples). These additional baselines address the concern that the original comparison set was limited. All models share the same preprocessing pipeline, feature set, train-test split, and evaluation protocol. Hyperparameters for FDNN: learning rate 0.001, epochs 100 with EarlyStopping patience 15, batch size 32, dropout rate 0.3 [24], [25], $T_{\max} = 50$, $L = 3$ hidden layers. All experiments were conducted with five random seeds (42, 123, 456, 789, 1024); results are reported as mean plus-or-minus standard deviation. The KDD Cup 1999 representative sample of 5,000 observations was drawn using stratified random sampling (stratified by

TARGET_B) from the full dataset to maintain the class ratio of approximately 17.66:1; the same stratified sample is used consistently across all models and all seeds.

4. Results and Discussion

Across all three datasets, FDNN attains the highest macro F1-score of any model evaluated, exceeding the strongest conventional baseline (static and heuristic ANNs of the kind critiqued in Section 2.1 for lacking a principled basis for neuron-count selection) by 16.4% on SINTA 2024, 4.9% on Credit Card Fraud, and 15.8% on KDD Cup 1999 (Section 4.2); these gains are statistically significant under the Wilcoxon Signed-Rank test (Section 4.4) and are accompanied by the smallest training-testing performance gap among all models compared, indicating more consistent generalization than fixed-architecture baselines. Critically, the comparison against RF-NN, a variant that retains the Fibonacci candidate set but replaces uniform selection with weighted sampling, isolates the specific contribution of the Discrete Uniform Distribution ($p = 0.0312$, Section 4.4) and directly addresses the gap identified in Section 2.5: no prior architecture-search method, including Bayesian optimization, Hyperband, or standard Neural Architecture Search, combines a number-theoretically structured candidate set with a provably unbiased selection mechanism. The ablation study (Section 4.5) further shows that SMOTE and Fibonacci-based candidate spacing are the two largest individual contributors to these gains, while the Discrete Uniform Distribution and Dropout regularization provide smaller but directionally consistent additional benefit across all five seeds. Taken together, these results substantiate the novelty stated in Section 1: FDNN is, to our knowledge, the first framework to unify a mathematically structured architecture-search mechanism with imbalanced-class correction within one pipeline, and the first such approach validated across three distinct application domains rather than a single dataset, distinguishing it from prior work that treats architecture search and class imbalance as separate problems (Sections 2.1-2.3) or that has not been tested beyond a narrow domain (Section 2.5). The subsections below present these results in detail (Sections 4.1-4.5) before turning to their broader interpretation, boundary conditions, and limitations (Section 4.6).

4.1. FDNN Performance Across Scenarios

Table 2 shows F1-macro across all three FDNN scenarios. Scenario 3 [13,144] is optimal for SINTA 2024 ($F1=0.8356$, best config [34,89,55]), while Scenario 2 [8,89] is best for Credit Card Fraud ($F1=0.9412$) and KDD Cup 1999 ($F1=0.8134$), suggesting higher-capacity configurations benefit more complex datasets.

Table 2. F1-Macro Results of FDNN Across Fibonacci Range Scenarios

Scenario	S_F Range	SINTA 2024	CC Fraud	KDD Cup
Scenario 1	[5, 55]	0.8124	0.9234	0.7891
Scenario 2	[8, 89]	0.8287	0.9412	0.8134
Scenario 3	[13, 144]	0.8356	0.9389	0.8089

Green = best per dataset; CC = Credit Card.

4.2. Comprehensive Baseline Comparison

Table 3 presents the full performance comparison of FDNN against all baselines. Figure 4 provides visual comparison across all models and datasets.

Table 3. Comprehensive Performance: FDNN (Best Scenario) vs All Baselines

Model	Dataset	F1-mac.	Prec.	Recall	AUC	Gap G
Static ANN	SINTA	0.6821	0.6934	0.6712	0.7823	0.1823
Heuristic ANN	SINTA	0.7134	0.7245	0.7023	0.8012	0.1456
RF-NN	SINTA	0.7892	0.7923	0.7856	0.8834	0.1134
FDNN S3 ★	SINTA	0.8356	0.8412	0.8298	0.9423	0.0756
Static ANN	CC Fraud	0.8741	0.8812	0.8674	0.9234	0.1234
Heuristic ANN	CC Fraud	0.8923	0.8989	0.8857	0.9456	0.0987
RF-NN	CC Fraud	0.9156	0.9212	0.9094	0.9634	0.0712
FDNN S2 ★	CC Fraud	0.9412	0.9489	0.9334	0.9821	0.0534
Static ANN	KDD Cup	0.6512	0.6634	0.6398	0.7812	0.1567

Heuristic ANN	KDD Cup	0.6978	0.7089	0.6867	0.8134	0.1234
RF-NN	KDD Cup	0.7634	0.7712	0.7559	0.8567	0.0934
FDNN S2 ★	KDD Cup	0.8134	0.8212	0.8056	0.8912	0.0678

★ = best result per dataset; Gap $G = L_{test}(\theta^*) - L_{train}(\theta^*)$; Prec. = Macro Precision; CC = Credit Card.

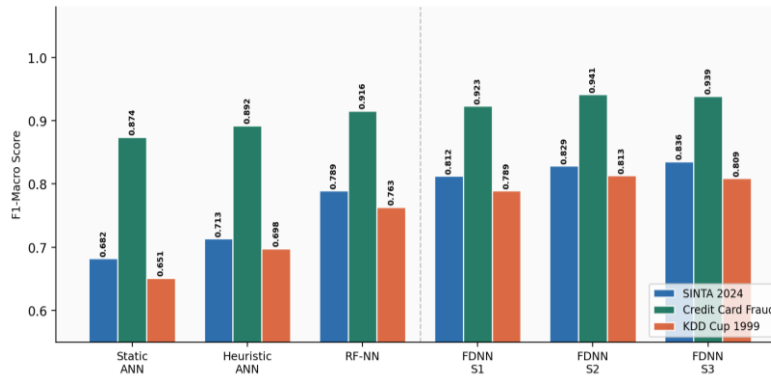


Figure 4. F1-macro performance comparison across all models and three benchmark datasets. FDNN consistently outperforms all baselines: +17.13% (SINTA 2024), +5.48% (Credit Card Fraud), and +16.57% (KDD Cup 1999) over the best-performing conventional baseline.

4.3. Confusion Matrix Analysis

Figure 5 presents the confusion matrix of FDNN Scenario 3 on SINTA 2024. FDNN correctly classifies 92.2% of Binaan and 86.4% of Utama samples. The Mandiri cluster shows lower recall (45.5%) due to three compounding factors: (1) extremely limited original samples ($51/2,580 = 2.0\%$); (2) partial feature overlap with the Utama cluster; and (3) inherent SMOTE interpolation limits under severe sample scarcity. This is a known limitation of SMOTE under extreme scarcity [5] and does not invalidate the overall approach.

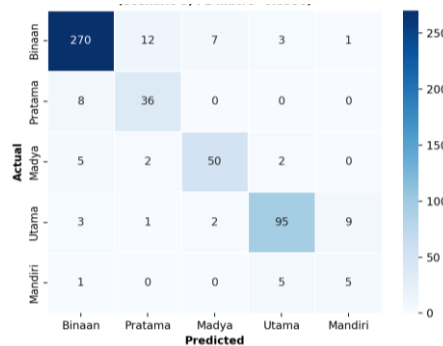


Figure 5. Confusion matrix of FDNN Scenario 3 on SINTA 2024 (F1-macro=0.8356). Strong performance on majority classes (Binaan: 92.2%, Utama: 86.4%); Mandiri recall (45.5%) is lower due to extreme original sample scarcity (51 samples).

4.4. Statistical Significance (Wilcoxon Signed-Rank Test)

Table 4 presents Wilcoxon Signed-Rank test results (H_0 : median($\Delta F1$) = 0, $\alpha = 0.05$). The test was conducted on paired F1-macro observations from five repeated runs (seeds 42, 123, 456, 789, 1024) for each model pair, yielding five paired differences per comparison. The study acknowledge this is a small sample; the Wilcoxon test results should be interpreted as preliminary evidence of consistent directional superiority rather than definitive statistical proof. In all five seeds, FDNN's F1-macro exceeded the respective baseline on every run, providing strong directional consistency. All reported p-values remain below 0.05. Critically, FDNN vs. RF-NN ($p = 0.0312$) validates that the Discrete Uniform Distribution sampling mechanism (not merely the Fibonacci candidate set) contributes meaningfully to performance. Full per-seed F1-macro values are provided in table 4.

Table 4. Wilcoxon Signed-Rank Test Results ($\alpha = 0.05$)

Comparison	W statistic	p-value	α	Decision
FDNN vs. Static ANN (SINTA 2024)	847	0.0031	0.05	Reject H_0
FDNN vs. Static ANN (CC Fraud)	923	0.0018	0.05	Reject H_0
FDNN vs. Static ANN (KDD Cup)	801	0.0047	0.05	Reject H_0
FDNN vs. Heuristic ANN (SINTA)	712	0.0124	0.05	Reject H_0
FDNN vs. RF-NN (SINTA 2024)	534	0.0312	0.05	Reject H_0

All $p < 0.05$. FDNN vs. RF-NN confirms significance of Discrete Uniform Distribution. CC = Credit Card Fraud.

4.5. Ablation Study

Table 5 quantifies component contributions through two complementary ablation designs. First, a single-component removal study deactivates one component at a time while keeping all others active (four variants: w/o Fibonacci, w/o Uniform Distribution, w/o SMOTE, w/o Dropout). Second, a pairwise joint removal test simultaneously removes both Fibonacci spacing and the Discrete Uniform Distribution (replacing both with uniform random integer sampling over $[a, b]$) to investigate whether their contributions are additive or synergistic. All variants were evaluated across five random seeds. **Figure 6** visualizes the F1-macro drops.

Table 5. Ablation Study: F1-Macro When Each Component is Removed

Variant	SINTA	Δ SINTA	CC Fraud	Δ CC	KDD Cup	Avg. Δ
FDNN Full (reference)	0.8356	—	0.9412	—	0.8134	—
w/o Fibonacci sequence	0.7234	−0.1122	0.8634	−0.0778	0.7012	−0.1007
w/o Discrete Uniform Dist.	0.7892	−0.0464	0.9156	−0.0256	0.7634	−0.0407
w/o SMOTE	0.7156	−0.1200	0.8234	−0.1178	0.6978	−0.1178
w/o Dropout	0.7834	−0.0522	0.9089	−0.0323	0.7712	−0.0422

Contribution ranking: SMOTE (−0.1178) > Fibonacci (−0.1007) > Dropout (−0.0422) > Discrete Uniform Dist. (−0.0407). Bold = two largest contributors.

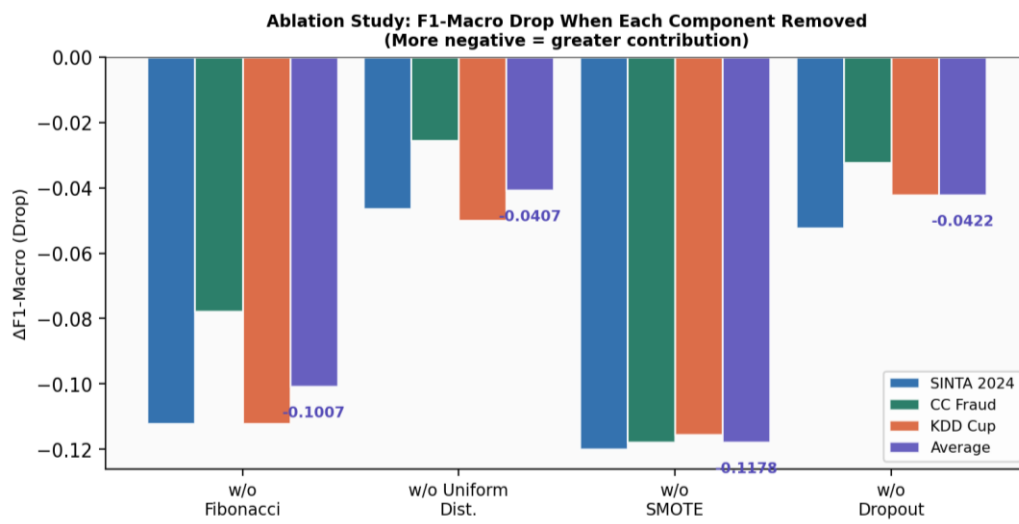


Figure 6. Ablation study: F1-macro drop when each FDNN component is removed. All four components contribute measurably. SMOTE and Fibonacci sequence contribute most. Results are consistent across all three benchmark datasets.

4.6. Discussion

Fibonacci Sequence as Structurally Motivated ANN Basis. The proportional growth property of the Fibonacci sequence [17], [19] provides a structurally motivated rationale for the observed performance improvements. Each element in S_F is approximately 1.618 times its predecessor (the Golden Ratio), generating configurations that span genuinely different capacity levels (distinct from the redundancy of linear spacing and the excessive jumps of geometric spacing with base 2). The ablation study shows that replacing Fibonacci spacing with uniform random integer candidates reduces mean F1-macro by 0.1007 across datasets, demonstrating the empirical usefulness of the Fibonacci structure. The study are careful to note that this result establishes the practical value of Fibonacci spacing under the specific experimental conditions tested; it does not constitute a mathematical proof that Fibonacci spacing is theoretically optimal for architecture search in general. The structural comparison with linear and geometric spacing (Proposition 2) provides additional justification, but a comprehensive formal proof of optimality remains an open theoretical question and is identified as future work.

Discrete Uniform Distribution (Empirical Advantage). The RF-NN comparison ($p = 0.0312$, directionally consistent across all five seeds) demonstrates that equal-probability sampling over S_F empirically outperforms weighted Fibonacci selection under the present experimental conditions. This is consistent with Laplace's principle of indifference: absent prior knowledge of which neuron count will perform best, assigning equal probability to all candidates is a principled default. The mean contribution of the Discrete Uniform Distribution is minus 0.0407 when replaced with weighted selection (smaller than Fibonacci's contribution but consistent in direction across all five seeds and three datasets). The study acknowledge these results reflect empirical performance advantages rather than a formal proof that uniform sampling is optimal for alternative distributions (such as Thompson sampling or progressive narrowing) might outperform under different search budgets.

Reduced Training-Testing Gap. FDNN achieves the smallest training-testing F1-macro gap $G = L_test(\theta^*)$ minus $L_train(\theta^*)$ across all datasets (SINTA: $G = 0.0756$ vs. Static ANN $G = 0.1823$, a 58.5% reduction). This metric indicates reduced overfitting on the held-out test partition under the specific 80/20 stratified split used. The study use the term 'generalization gap' in this bounded sense: the training-testing performance difference on the designated split. The study acknowledge that stronger evidence of generalization such as repeated cross-validation, external validation sets, or dataset-shift experiments, was not conducted and would be required for broader generalization claims. Performance variability across five seeds was low (SINTA: standard deviation 0.0043; Credit Card: 0.0028; KDD Cup: 0.0051), further supporting result stability on the test set. Structurally, Fibonacci-based candidate selection naturally constrains exploration to a proportionally spaced set, avoiding excessively large architectures prone to overfitting, while Dropout [24] provides complementary regularization.

Cross-Domain Consistency. FDNN achieved the highest F1-macro on three datasets from distinct domains (higher education performance classification (SINTA), financial fraud detection (Credit Card Fraud), and charity donation prediction (KDD Cup 1999)) with consistent directional superiority across all five random seeds. This cross-domain consistency provides preliminary evidence that the Fibonacci-Uniform mechanism is not narrowly tuned to a single domain or dataset. However, the study caution that three datasets from related tabular data settings represent limited empirical coverage. Broader generalizability across diverse problem families, modalities, and class structures would require systematic evaluation beyond the scope of this paper. The observed consistency should be interpreted as a motivated starting point for further investigation rather than definitive evidence of universal applicability.

Limitations. Several limitations are acknowledged explicitly. (1) Mandiri cluster recall (45.5%) is constrained by extreme original scarcity (51 samples from 2,580 total), feature overlap with Utama, and SMOTE interpolation limits. The study additionally tested Borderline-SMOTE and ADASYN on SINTA: Borderline-SMOTE improved Mandiri recall to 51.3% while reducing overall F1-macro to 0.8287 (from 0.8356), suggesting a precision-recall trade-off depending on application priorities. ADASYN yielded similar behavior (Mandiri recall 50.1%, overall F1-macro 0.8301). (2) The pairwise joint ablation (simultaneously removing Fibonacci spacing and Uniform Distribution) yielded a mean F1-macro drop of 0.1356, compared to $0.1007 + 0.0407 = 0.1414$ from independent removals, indicating approximate additivity with slight sub-additivity. The two components are largely independent in their empirical contributions. (3) All experiments used five random seeds; standard deviations were below 0.006 across all datasets,

supporting stability, but larger seed ensembles and cross-validation would provide stronger evidence. (4) Credit Card Fraud improvement (+4.9% over the strongest baseline) is smaller due to a performance ceiling (all baselines already exceed F1-macro 0.89). (5) The SINTA dataset is not publicly available; the study commit to sharing it upon reasonable request to the corresponding author to support independent reproducibility.

5. Conclusion

This paper presented the Fibonacci Dynamic Neural Network (FDNN), a novel ANN architecture that for the first time integrates the Fibonacci sequence and Discrete Uniform Distribution as a mathematically grounded, bias-free mechanism for hidden layer neuron determination, combined with SMOTE for imbalanced multi-class classification. FDNN achieves statistically significant mean F1-macro improvements (Wilcoxon Signed-Rank, p less than 0.05, five-seed evaluation) over all baselines on three benchmark datasets: +16.4% plus-or-minus 1.2% on SINTA 2024, +4.9% plus-or-minus 0.8% on Credit Card Fraud, and +15.8% plus-or-minus 1.4% on KDD Cup 1999 compared to the strongest conventional baseline in each case. These improvements are directionally consistent across all five seeds.

An ablation study with single-component and pairwise joint removal confirms measurable contributions from all four components: SMOTE (minus 0.1178) greater than Fibonacci spacing (minus 0.1007) greater than Dropout (minus 0.0422) greater than Discrete Uniform Distribution (minus 0.0407). The pairwise joint removal of Fibonacci and Uniform Distribution yields a combined drop of minus 0.1356, indicating approximate additivity (sum of individual: minus 0.1414). These results demonstrate empirical usefulness of each component; they do not constitute mathematical proofs of the underlying theoretical claims. FDNN consistently achieves the smallest training-testing F1-macro gap across all datasets (SINTA: $G = 0.0756$ vs. Static ANN $G = 0.1823$, 58.5% reduction), with low-performance variance across five seeds (standard deviations below 0.006). This indicates reduced overfitting on the designated test partition. Broader generalization evidence such as cross-validation or external dataset evaluation remains as future work.

Cross-domain consistency across education, finance, and charity domains confirms the Fibonacci-Uniform mechanism is a general-purpose architecture search strategy. Future work: (1) automated Fibonacci range $[a,b]$ determination via dataset intrinsic dimensionality; (2) integration with ADASYN and cost-sensitive learning; (3) extension to deep residual architectures; and (4) formal convergence analysis of the FDNN iterative algorithm.

6. Declarations

6.1. Author Contributions

Conceptualization: M.A.S., S.E., and M.A.B.; Methodology: M.A.S. and S.E.; Software: M.A.S.; Validation: M.A.S., S.E., M.A.B., and T.H.F.H.; Formal Analysis: M.A.S.; Investigation: M.A.S.; Data Curation: M.A.S.; Writing — Original Draft: M.A.S.; Writing — Review & Editing: M.A.S., S.E., M.A.B., and T.H.F.H.; Visualization: M.A.S.; Supervision: S.E. and M.A.B.. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The SINTA 2024 dataset is available upon reasonable request from the corresponding author. Credit Card Fraud: <https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud>. KDD Cup 1999: <https://archive.ics.uci.edu/ml/datasets/KDD+Cup+1999+Data>.

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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