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Predicting Small Business Longevity and Competitiveness Through Self - Random Manhattan Botox - Coupled Attention Network Driven Strategic Entrepreneurship

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Abstract

The dynamics between the financial, operational, strategic, and environmental factors that influence a small business' longevity and competitiveness can be extremely complex and nonlinear in nature. Current predictive approaches generally do not provide adequate accuracy or adaptability over time by capturing these multidimensional dependent variables. Consequently, the purpose of this research study is to develop a new deep learning framework, called Self-Random Manhattan Botox Coupled Attention Network (Self-RanMB-CAN), for the purpose of generating robust predictions of small business longevity and competitiveness. This framework is used in conjunction with structured datasets called the Small Business Longevity Dataset, which contains 500 records, and captures 12 key features of each small business. In preparation for using the proposed framework with these datasets, CCFA (Cumulative Curve Fitting Approximation) is applied to preprocess the data to normalize and ensure the consistency of trends within the dataset prior to performing feature extraction using DCKTKT (Discrete Cosine-Krawtchouk–Tchebichef Transform) to maintain both the spectral and spatial characteristics of each feature. A combination of an RCNN (Random Coupled Neural Network) and a Manhattan Self-Attention (MaSA) framework provides greater attention to business variables that are most impactful and thus improve feature selection. In addition, the Botox Optimization Algorithm (BOA) optimizes network parameters, which increases convergence stability. The experimental results show a classification accuracy of 99.9%, along with high precision, recall, and F1-scores; thus, the proposed framework significantly outperformed several benchmark models. The research results indicate that the proposed system can accurately model complex business dynamics and facilitate reliable predictive decision-making. In summary, the Self-RanMB-CAN is a scalable and accurate intelligent decision-support tool for strategic entrepreneurship and helps to provide a better understanding of business survival and competitive behavior in an uncertain marketplace.

Keywords: Small Business Longevity, Strategic Entrepreneurship, Random-Coupled Neural Network, Manhattan Self-Attention, Botox Optimization Algorithm, Cumulative Curve Fitting Approximation (CCFA), Discrete Cosine-Krawtchouk–Tchebichef Transform.

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Introduction

In Indonesia, Micro, Small, and Medium Enterprises (MSMEs) make up 98.8 % of all businesses; these enterprises provide 97 % of Indonesia's workforce, and contributed 60.3 % of the nation's gross domestic product in 2018. However, 15.90 % of these enterprises use the internet, and 8.53 % have computers; the remaining enterprises are still working within traditional parameters. The results of the pilot study indicated that founders and current business operators expressed the most concern regarding sustainability and continuity; information and technology play a large role (Abad-Segura et al., 2025; Kesa, 2023). Additionally, Entrepreneurship contributes to the social welfare and financial stability of Indonesia by providing jobs and supporting the economy of this country. The rate of entrepreneurial activity in Indonesia in the year 2020 was 3.47 % compared to 8.47 % in Singapore, 4.26 % in Thailand, and 4.74 % in Malaysia (Ebose et al., 2025; Ezeife et al., 2024). In 2010, small businesses had 5–19 employees and accounted for 60.3 % of the GDP of Indonesia; since that time, these businesses have experienced rapid growth. However, as a result of the global pandemic, the sales prices of goods have significantly declined, and the revenues and profits of small businesses have declined by 70 % (Conz et al., 2024; Dieperink et al., 2025).

Also related to the effects of the recession on small business failure, bad loans, lost jobs, and impacts on supply and demand to come; Community Economic Development research is needed to understand how the changes in firm entry and exit dynamics impact the economic growth of local communities (Andersson et al., 2022; Claudia & Wijaya, 2023). Much research to date has found that location is a key factor in whether or not a business survives and that there are particular aspects of location (for example, site selection and proximity to concentrations of skilled labor) impacting a company's ability to remain viable. However, in terms of empirical studies, there has been little research into the viability of rural businesses within municipalities (Geissdoerfer et al., 2022; Tillmar et al., 2022). A longitudinal study of data from the period 2007 – 2017 found that the survival rates for manufacturing, transportation, and wholesale firms were much higher when located within a 1/2 mile of a highway entrance or exit ramp. Furthermore, younger businesses located near older ramp sections of the U.S. highway systems had a higher chance of survival compared to businesses that were located near downtown areas and cultural hubs (Grissa & Lakhal, 2023; Van Leuven et al., 2023). The ways that businesses develop or innovate their business models in business-to-business (B2B) relationships are primarily through piloting, experimenting, and prototyping; however, the conceptual differences between these processes are not entirely clear (Jahmurataj et al., 2023; Jing et al., 2025; Kupangwa et al., 2023).

There is much uncertainty in measuring how long small businesses last, due to many internal and external factors such as financial stability, market dynamics, structural planning, and innovation capabilities. The inability of traditional predictive models to measure the interdependencies of these factors has resulted in a lack of precision in estimating both how long a business lasts and its competitive ability, resulting in very poor adaptability and accuracy. To assist the strategic entrepreneur in making sound decisions based upon an overall confidence of how a business's characteristics can affect future outcomes, an immediate need exists for a framework that is based on learning from historical data.

Novelty and Contribution

The novelty and contribution of this work are given below:

- The Self-RanMB-CAN deep learning architecture is a new combination of the Random Coupled Neural Network (RCNN) and the Manhattan Self-Attention (MaSA) that was created using a method referred to as the Botox Optimization Algorithm (BOA).
- The CCFA technique for pre-processing is presented as a means of normalizing and enhancing temporal business behavior trends.
- Uses both spatial and frequency information for feature extraction. (Hybrid Transformation Method; DCKTKT) to achieve enhanced performance.
- Enhanced model performance due to targeted attention to important business features, resulting in stable models using data validation for models.

The organization of the remainder of this document proceeds as follows: Section 2 discusses an extensive literature review examining the current state of research on the longevity of small businesses and their competitiveness, including important methods employed, findings, and gaps in the current body of literature. Section 3 describes the proposed methodology, including the system workflow, mathematical formulation, and algorithmic framework for the proposed Self-RanMB-CAN Model in detail. Section 4 provides details regarding the entire experiment from set-up, through results collected from the experiment, and finally a discussion of those results, including performance evaluations, comparisons to other methods, and an ablation study which provides evidence of the effectiveness of the proposed method. Finally, Section 5 provides a summary of this research study, identifying possible future research directions to improve the applicability and effectiveness of the proposed framework when applied to actual businesses.

Literature Survey

Various research has been done relating to the sustainability and longevity of small businesses utilizing analytical, behavioral, and computational methods. One research area has been the role of organizational learning behavior on the survival and continued existence of SMEs. The literature shows that SMEs that develop and/or adopt adaptive learning-centric behaviors have greater operational capabilities than those without such behaviors when operating in high uncertainty, as well as greater resiliency to disruptions in the marketplace Liu et al., 2024). Also, entrepreneurial behavior associated with bricolage-type strategies is another important mechanism for addressing operational constraints, which allows small businesses to use limited resources creatively and effectively in order to remain viable and competitive (Matindike et al., 2024).

In conjunction with behavioral perspectives, Technology-based Systems (such as CRM) are widely acknowledged to facilitate the improvement of business performance. According to empirical research, strategic adoption of CRM can significantly boost customer engagement and operational effectiveness/efficiency and improve strategic decision-making; therefore, this leads to greater profitability and sustainable operations for SMEs (Martinho et al., 2025). Reduction of an SME has a positive effect on their ability to make quality decisions, develop better approaches to resolving problems, and sustain the long-term viability of SME in very competitive settings (Ndlela et al., 2024).

Strategic development (e.g., research & development) as well as creating innovative approaches for developing new product ideas are integral factors in establishing a competitive position in the market. Studies of the transportation and logistics industries have shown that clearly defined competitive strategy implementation can lead to improved operational efficiency and other benefits over an extended period of time within a dynamic business environment (Pogodina et al., 2022). Likewise, utilizing modern innovation & technology management techniques plays an important role in remaining competitive; organizations that have an ongoing commitment to incorporating technological advancements into their operations are more likely to achieve long-term market relevance and survival compared to those that do not (Parajuli et al., 2023).

Firms with so-called sustainable innovation capacities are perceived as having an essential role in increasing competitiveness in family-business systems operating in emerging markets, and, therefore, innovation-oriented firms possessing or utilizing a sustainable form of innovation relative to those firms that do not or utilize a more traditional form of innovation have been found to be associated with enhanced competitive advantage and a greater likelihood of long-term success (Rexhepi et al., 2024).

Research shows that the competitive advantage and lasting success of a small enterprise can be shaped by its learning orientation, adaptive resources, ability to think critically, and develop a strategic plan for innovation. Various studies illustrate how utilizing CRM systems and proper technology management is helpful in improving operational efficiencies and making good decisions. The development of sustainable innovation capabilities is also helpful to long-term survival in a highly competitive or uncertain environment. In summary, there is a body of literature that shows there are many interconnected behavioral and technological factors that have an impact on the sustainability of an organization, therefore requiring advanced models to adequately explain the complexity of the relationship between them.

Problem Statement

Many small businesses struggle to remain in business over time, primarily because of uncertain conditions in their environment. The failure of some small businesses is compounded by their financial situations, market conditions, strategic plans, and ability to innovate. Current predictive models typically do not adapt well to changes in the environments for which they were developed, or they do not produce sufficiently accurate information to support long-term planning for small firms experiencing uncertainty. Small businesses need a predictive framework that generates accurate forecasts based on multiple independent variables to assist the entrepreneur with making wiser decisions when developing strategic plans. This research explores these issues and outlines a methodology for conducting this type of research.

Proposed Methodology

System Workflow of the Proposed Self-RanMB-CAN Framework

This section presents a novel deep learning framework titled Self-random Manhattan Botox coupled Attention network (Self-RanMB-CAN), aimed at enhancing prediction accuracy for small business longevity and competitiveness, which is explained. The workflow diagram in fig. 1 presents the Self-RanMB-CAN. An organized dataset called the Small Business Longevity Dataset with 500 records and 12 important features has been created to help in carrying out this analysis. Data then undergoes the process of pre-processing based on Cumulative Curve Fitting Approximation (CCFA) in ensuring the normalization of trend representation and feature extraction through encapsulation at the level of extraction involving the use of Discrete Cosine-Krawtchouk Tchebichef Transform (DCKTKT). The suggested Self-RanMB-CAN combines a Random-Coupled Neural Network (RCNN) with Manhattan Self-Attention (MaSA), which gives priority to salient features, and then the Botox Optimization Algorithm (BOA) is used to optimize network parameters to obtain better performance.

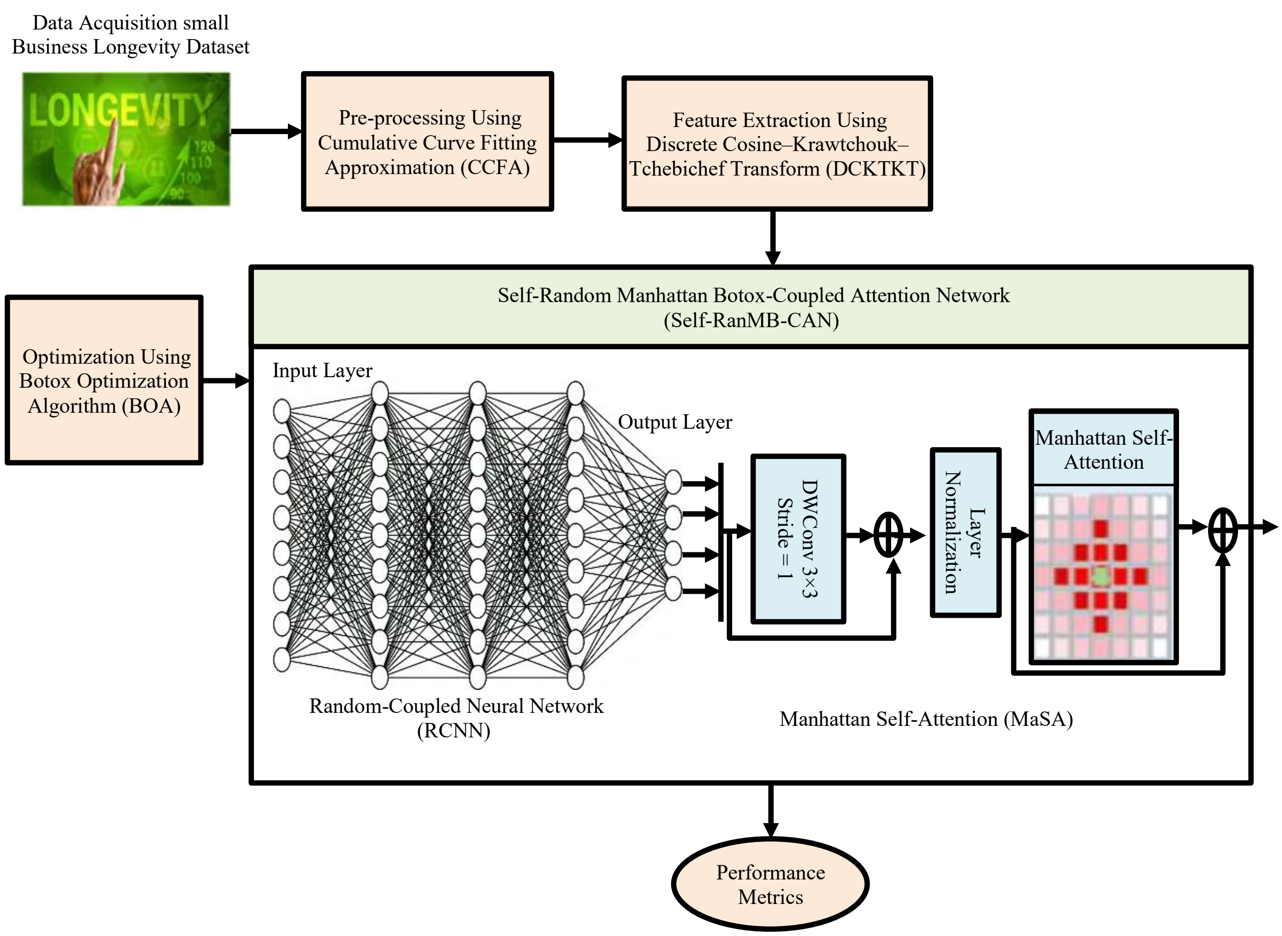


Fig. 1: Workflow Diagram of the Self-RanMB-CAN

Mathematical Description of the Proposed Self-RanMB-CAN Framework

The Self-Random Manhattan Botox coupled Attention Network (Self-RanMB-CAN) enhances long-term success predictions for small businesses through pre-processing, feature extraction, attention-based learning, and adaptive optimization. The first step in predicting long-term success is to apply Cumulative Curve Fitting Approximation (CCFA) as a normalization technique to the business dataset to mitigate inconsistencies in the features and provide a better representation of their trends. Once normalized, the business feature vector is represented as follows:

$$C_i = \frac{X_i - \mu}{\sigma} \tag{1}$$

Where X_i denotes the input business feature vector, while μ and σ represent the mean and standard deviation of business attributes. Equation (1) performs feature normalization and improves data consistency before training.

Once the data has been preprocessed, the DCKTKT produces optimized business representations using the normalized features of the data set. The transformation of features into coefficients is calculated using:

$$F_i = \sum_{p=0}^{M-1} \sum_{q=0}^{N-1} C_i cos\left(\frac{(2p+1)q\pi}{2N}\right) \qquad (2)$$

Where $F_i$represents the extracted business feature vector. Equation (2) preserves significant spectral-spatial business characteristics and improves feature discrimination capability.

A Random-Coupled Neural Network that integrates Manhattan Self-Attention takes the extracted feature coefficients and generates a prediction based on the combination of those features; therefore, this model predicts an accurate result. The prediction equation can be represented in the following manner:

$$\hat{L}_{cat} = Softmax(MaSA(RCNN(F_i))) \qquad (3)$$

RCNN is a Random-Coupled Neural Network Learning, and MaSA is Manhattan Self-Attention. Equation (3) predicts the longevity of Businesses based on the main features of the Business through the learning of Feature Weights for Businesses.

Algorithmic Framework of Self-RanMB-CAN

Algorithm 1: Self-RanMB-CAN for Small Business Longevity Prediction

Input:

B_{id}: Business Identifier

Y_{op}: Years in Operation

A_{rev}: Annual Revenue

N_{emp}: Number of Employees

M_{comp}: Market Competitiveness

I_{idx}: Innovation Index

D_{pres}: Digital Presence

S_{plan}: Strategic Planning

E_p: Training Epochs

Output:

$\hat{L}_{cat}$: Predicted Longevity Category

$Acc, F1$: Performance Metrics

Pseudocode:

Load Small Business Longevity Dataset

Split the dataset into training and testing samples

FOR each business sample

  Normalize feature values using CCFA

END FOR

Generate transformed business features using DCKTKT.

Initialize RCNN network parameters

FOR epoch = 1 to E_p

  Train RCNN using transformed feature vectors.

Compute Manhattan attention scores

Assign attention weights to important business features

Update network weights using BOA optimization

END FOR

Predict business longevity category $\hat{L}_{cat}$

Compute Accuracy and F1-score

Return optimized prediction results

The operational workflow of the Self-RanMB-CAN framework, as outlined in Algorithm 1, provides accurate predictions about the longevity and competitiveness of small businesses. The initial step is to load in the Small Business Longevity Dataset, then separate it into training and test samples. Next is to preprocess the dataset using CCFA to normalize the value of each business feature within that dataset; thus, this helps define a consistent dataset. Finally, create optimally-spectral/spatial representations of each of the business features by applying DCKTKT transformations to each of these transformed datasets. Next, the Random-Coupled Neural Network uses the transformed features to learn nonlinear business behavior patterns. The Manhattan Self-Attention mechanism calculates attention scores and assigns adaptive weights to the most influential business attributes. The Botox Optimization Algorithm iteratively updates all of the network's weights to improve the overall prediction performance and reduce the classification error, continuing until the training process is complete. After the training process is finished, the optimized framework predicts the business longevity category and evaluates the overall performance based on evaluation metrics such as Accuracy and F1-score.

Results and Discussions

In this section, the results and discussions of the Self-random Manhattan Botox coupled Attention network (Self-RanMB-CAN) for enhancing prediction accuracy for small business longevity and competitiveness are discussed here.

Software Details

The framework (SelfRanMB-CAN) presented within this publication was implemented in Python (v 3.7) because of its excellent capabilities for data science and deep learning applications. The model's Random-Coupled Neural Network (RCNN) and Manhattan Self-Attn (MaSA) components were built using the TensorFlow and Keras libraries; the data preprocessing, data manipulation, and working with the dataset were done using the NumPy and Pandas libraries. The feature extraction processes were done using CCFA and DCKTKT implementations from the SciPy library, and using custom Python functions to perform high-level numerical analysis. Using the Scikit-learn library, several performance evaluation metrics (Accuracy, Precision, Recall, F1-score, MSE, RMSE) were computed; results were visualized and compared using Matplotlib. The experiments were carried out on a system running Windows 10, and the Botox Optimization Algorithm (BOA), which was implemented through a custom optimization module added to Python, enabled efficient parameter tuning and model optimization.

Dataset Description

In this study, a dataset titled "Small Business Longevity Dataset" has been constructed to support predictive modeling of small business longevity. The dataset comprised 500 records, each representing an individual business entity. A total of 12 distinct features are included: Business ID (unique identifier), Years in Operation (business age in years), Annual Revenue (income in USD), Number of Employees (total workforce), Industry Sector (business category such as Retail, IT Services, Healthcare, etc.), Market Competitiveness (level of competition—Low, Medium, or High), Innovation Index (normalized index between 0 and 1), Owner Education Level (qualification of business owner), Digital Presence (online presence status), Funding Type (source of financial support), Strategic Planning (planning horizon—Short-term to Long-term), and Longevity Category (the target label indicating business longevity classified as Low, Moderate, or High). The synthetically generated data enable empirical analyses of the factors affecting the sustainability and survival of small businesses. The split between the 80% of data used to train models and the other 20% used to test models has been made.

Parameter Initialization

Table 1 shows the major parameters used to implement the Self-RanMB-CAN Framework, including how the Self-RanMB-CAN architecture is created. It also provides details around how the architecture is implemented using three modes of data: what data is used for model training, evaluation, and testing; as well as any pertinent information about the OS environment (Windows 10) and BOA. The experimental setup consisted of a stable Windows 10 computer system where all experiments were conducted with the Botox Optimization Algorithm (BOA) as the primary weighting method, which aided in the tuning of the self-weights of the network model. Lastly, the model is built on the "Small Business Longevity Dataset" that contains various structured variables related to businesses and their classification as long-term businesses. Each of the implementations was done with the assistance of Python 3.7, which has excellent support for deep learning architectures and has numerous libraries available for numerical and scientific computations.

Table 1: Implementation Parameters

Parameters	Description
Proposed Neural Network	Self-RanMB-CAN
OS	Windows 10
Optimization	BOA
Dataset	"Small Business Longevity Dataset"
Software	Python 3.7

Performance Metrics

In this paper, the performance of the Self-RanMB-CAN method is compared with the performance of 6 different techniques, including MSME (Liu et al., 2024), NSM (Matindike et al., 2024), SME (Martinho et al., 2025), CM-IPASD-MSB (Ndlela et al., 2024), STI (Pogodina et al., 2022), QM (Parajuli et al., 2023), B2BBM (Rexhepi et al., 2024), as measured by performance metrics such as mistake rate, recall, f1 score, accuracy, precision, train time, computational complexity, processing time, Hamming loss, RMSE, MSE, MAE, MAPE. In table 2, equations for each of these performance metrics are given.

True Positive (TP)**:** accurately identify profitable companies, allowing for effective support and strategic planning.

False Positive (FP): Falsely classifying failing companies as viable results in resource waste and bad choices.

False Negative (FN)**:** Ignores profitable companies, resulting in lost chances and untapped potential.

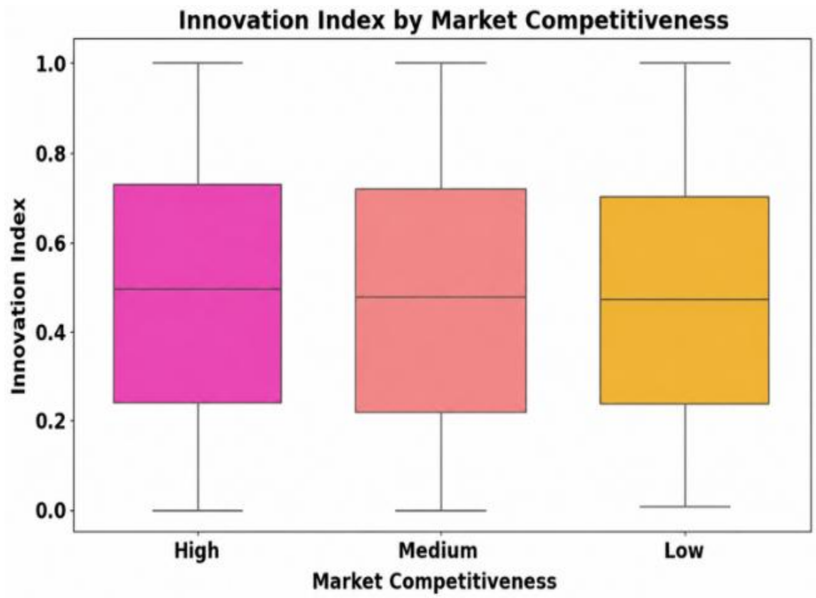
True Negative (TN) **:** accurately identifies unsustainable companies to avoid wasting resources and giving false hope. Table 2 shows the Performance metrics from equations (4)-(8).

Table 2: Performance Metrics

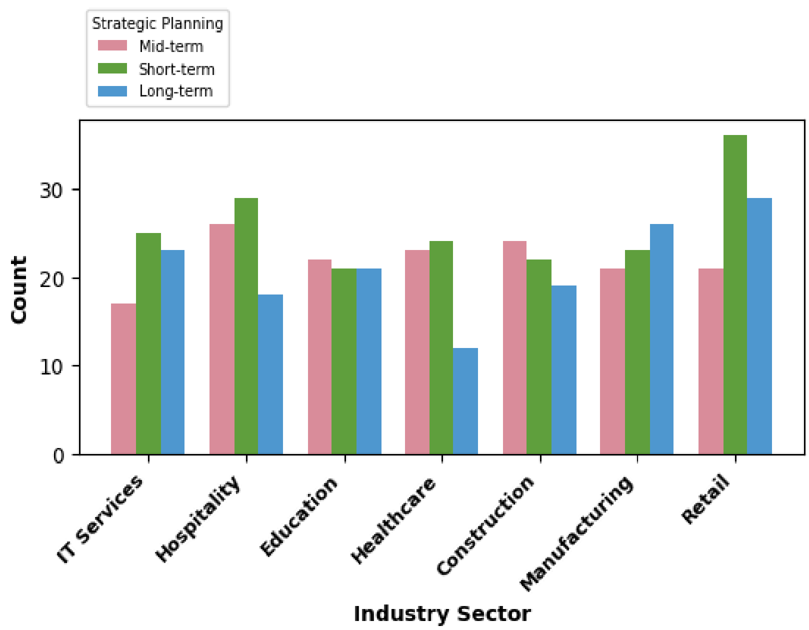
Performance Metric	Equations
Accuracy	$Accuracy = (TP + TN)/(TP + TN + FP + FN)$ (4)
Precision	$Precision = TP/(TP + FP)$ (5)
Recall	$Recall = TP/(TP + FN)$ (6)
F1-Score	$F1 - Score = (2 \times Precision \times Recall)/(Precision + Recall)$ (7)
Specificity	$Specificity = TN/(TN + FP)$ (8)

Performance Analysis

The performance analysis of Self-RanMB-CAN is discussed here:



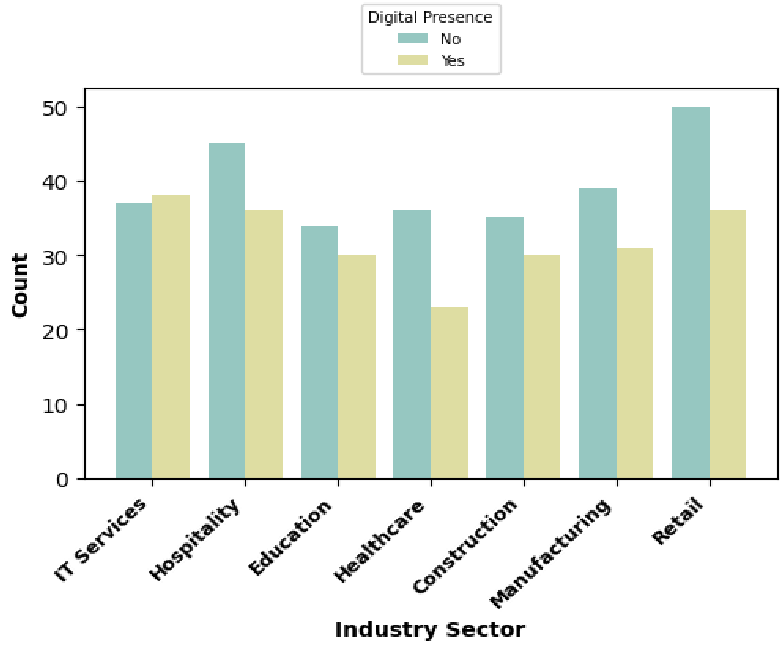
(a)



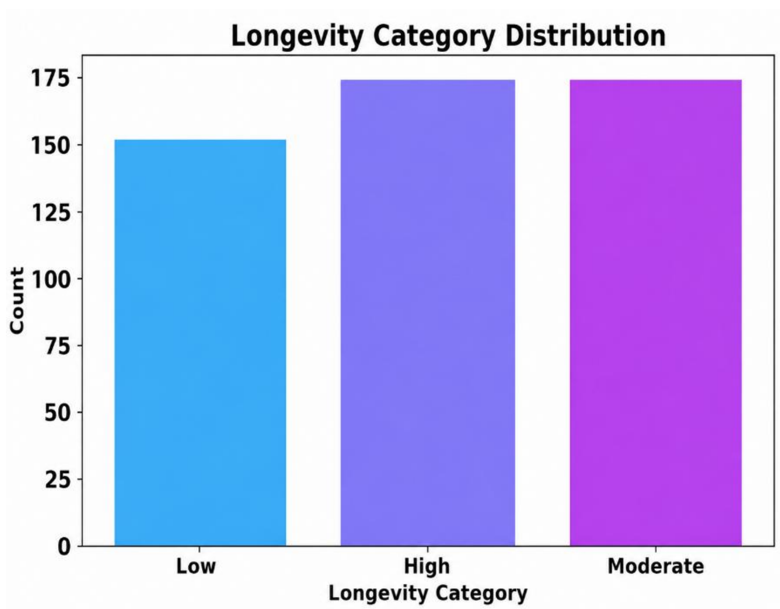
(b)

Fig. 2(a): Innovation Index by Market Competitiveness, 2(b) Strategic Planning Across Industry Sectors

Fig. 2 shows the (a) Innovation Index by Market Competitiveness and (b) Strategic Planning across Industry Sectors. When contrasted with their counterparts from lower competition industries, businesses in high-competition industries score better on the innovation index, as seen in fig. 2(a). In addition, fig. 2(b) shows how different industries utilize different strategies to strategically plan for future success: for example, retail companies have a tendency to think longer term compared to the amount of time that IT services or hospitality businesses think about in short-term periods. All together, this data demonstrates that the context of an industry and the pressure of the marketplace may have a significant impact on small firms' levels of innovation and strategic vision.



(a)



(b)

Fig. 3(a): Digital Presence by Industry Sector, 3(b) Longevity Category Distribution

Digital presence by industry in fig. 3 primarily reflects the number of companies within those industries that have established a digital presence (i.e., those that use digital technologies) as well as their likelihood to do so. As can be seen in fig. 3(a), both retail and information technology (IT) services have a larger presence compared to many of the other sectors, indicating that they are generally considered more digitized than other sectors (though this may not necessarily be an accurate representation). In contrast, manufacturing and construction have proportionally less digitization than either retail or IT services, as reflected in fig. 3(b). Furthermore, there are more companies within the higher and moderate lifetime categories than there are within the lower category; hence, there appears to be a reasonably balanced distribution of longevity within small businesses, which may indicate an increasing focus on sustainability.

Table 3: Overall Performance of the Suggested Approach in Contrast to Existing Methods

Metrics	MSMEs Liu et al., (2024)	NSM Matindike et al., (2024)	SMEs Martinho et al., (2025)	CM-IPASD-MSB Ndlela et al., (2024)	STI Pogodina et al., (2022)	QM Parajuli et al., (2023)	B2BBM Rexhepi et al., (2024)	Self-RanMB-CAN (Proposed)
Accuracy	97.26	76.61	88.90	76.89	83.35	93.32	88.37	99.97
Recall	95.76	93.32	77.45	81.70	97.81	92.30	86.41	98.92
Precision	94.44	93.55	97.67	87.90	92.13	93.94	78.21	99.12
Specificity	92.12	80.15	94.12	91.25	92.66	93.39	87.45	99.08
F1-Score	79.59	96.92	98.45	89.87	93.89	93.65	93.90	99.01
MSE	5.6	4.4	7.6	2.5	7.7	3.5	5.7	1.2
MAE	6.1	7.3	3.5	4.7	1.9	2.0	5.2	0.9
RMSE	7.2	3.4	6.6	7.8	2.7	2.2	5.4	1.1
AAE	8.7	5.3	6.5	7.6	8.4	4.2	3.2	0.7

Table 3 shows the Overall performance of the suggested approach in contrast to existing methods. With the best accuracy (99.97%), precision (99.12%), and F1-score (99.01%), the suggested Self-RanMB-CAN model performs better than current approaches in all important parameters, suggesting enhanced prediction abilities for the lifespan of small businesses. The Self-RanMB-CAN also has lower error estimates than other competitive models (MSE=1.2, MAE=0.9, RMSE=1.1, AAE=0.7) and high corresponds well to a very high % recall (98.92%) with the corresponding specificity of 99.08%. Compared to other predictive models like NSM (Matindike et al., 2024) or CM-IPASD-MSB (Ndlela et al., 2024), Self-RanMB-CAN provides consistent and reliable performance as a basis for making strategic decisions.

Table 4: Ablation Study

Model Configuration	RCNN	MaSA	BOA	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Baseline (without BOA)	✓	✓	✗	97.84	96.52	94.50	95.82
RCNN Only	✓	✗	✗	94.25	92.80	87.32	89.95
MaSA Only	✗	✓	✗	93.74	90.25	88.90	89.57
RCNN + BOA	✓	✗	✓	95.61	94.00	90.14	91.78
MaSA + BOA	✗	✓	✓	96.22	95.23	91.43	93.29
Full Model (Self-RanMB-CAN)	✓	✓	✓	99.97	99.12	98.92	99.01

Table 4 details the results of the Ablation Study. The ablation study shows how much each component of the Self-RanBMCANN model contributes to the performance of the model. The performance of the model is reduced when BOA is removed from the model; this indicates that BOA has an important effect on the performance of the overall model. When only using either RCNN or MaSA to make predictions, the accuracy and F1-score of the model significantly decrease, whereas when you combine either of those models with BOA, you see an increase in performance, specifically recall and precision. The optimal accuracy (99.97%), precision (99.12%), recall (98.92%), and F1-score (99.01%) come from using the entire model (RCNN + MaSA + BOA) to predict the lifetime of small businesses, which indicates that the combination of all the components of the model gives you the best performance when predicting the lifetime of a small business.

Discussion

The suggested Self-RanMB-CAN framework exhibits great potential to capture the intricate and mutually dependent traits of small business sustainability and competitiveness. Established forecasting methods typically have difficulty modeling the nonlinear relationships that exist among strategic planning, financial stability, innovation ability, and market dynamics. Conversely, the combination of Random-Coupled Neural Networks (RCNN's) with Manhattan Self-Attention (MaSA) allows for enhanced focus on the most impactful features of businesses by willfully reducing irrelevant (or less informative) data. The focused learning of features enhances the quality of representation and the likelihood of predictive accuracy. Meanwhile, the use of cumulative curve fitting approximation (CCFA) makes heterogeneous business data consistently normalized, and the use of discrete cosine-Krawtchouk-Tchebicheff transform (DCKTTKT) makes the features more diverse through preservation of both spectral and structural properties of the data set.

The experimental results demonstrate that the performance of the model generated by this architecture is significantly better than all existing benchmark models for all evaluation metrics, therefore validating the architecture's efficacy (including accuracy, precision, recall, and F1-score). In addition, the results show that the model is also very reliable at differentiating between the small businesses with different longevity categories. The ability of BOA to ensure optimal parameter tuning and improved convergence characteristics enhances the reliability of the model by decreasing the likelihood of overfitting arising from poorly tuned model parameters. In addition, results from the ablation study indicate that all of these elements fundamentally improve performance as well, such that the entire integrated model is better than its component(s). More importantly, Self-RanMB-CAN can serve as an important decision-support tool for entrepreneurs and policy makers because it allows for the early detection of businesses that are at risk and identifies the major factors for their sustainability. Therefore, Self-RanMB-CAN has great value for strategic planning, risk mitigation, and competitiveness in uncertain, fast-changing marketplaces.

Conclusion and Future Work

The Self-RanMB-CAN (The self-randomized Manhattan Botox Coupled Attention Network) is an innovative framework for predicting the longevity and competitiveness of small businesses. The study used a structured dataset to collect 500 instances of small business data using 12 key attributes. The proposed method utilizes a CCFA-based fractional model to allow for normalization of business trend data and increase accuracy in recorded data prior to invoking DCKTKT feature extraction methods to ensure preservation of spectrally and spatially represented characteristics of a small business. Ultimately, the core learning architecture of the framework, comprised of Random-Coupled Neural Networks (RCNN) and Manhattan Self-Attention (MaSA), allows for selective weighting of entrepreneurial characteristics such as financial stability, innovative capability, and strategic planning. To enhance the optimization of parameters and provide improved convergence stability, the Botox Optimization Algorithm (BOA) was used during model training. The experimental validation demonstrated the effectiveness of the hybrid architecture, producing a maximum classification accuracy of 99.9% as well as higher values for precision, recall, and F1-score than previously established benchmark models.

The Self-RanMB-CAN framework can be applied to larger, more heterogeneous real-world datasets in order to increase generalization across various economic contexts and industries. To increase predictive adaptability to rapidly changing conditions, additional investigation into adding macroeconomic indicators like inflation levels, changes in demand in the marketplace, and changes in public policy would be beneficial. Hybrid optimization methods may also be researched as a way to increase convergence speed and stability within the model.

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