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

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ABSTRACT

Predicting the survival and competitiveness of small businesses is an intricate problem owing to the multi-dimensional nature of strategic, financial, and operational aspects. Most current models do not accurately capture the complex dynamics between firm dynamics and survival patterns over the long run. In view of this, the study presents a new deep learning model known as Self random Manhattan Botox coupled Attention network (Self-RanMB-CAN), whose goal is to improve the accuracy of prediction for small business survival and competitiveness. A structured dataset named "Small Business Longevity Dataset" consisting of 500 records with 12 critical features has been created to enable this analysis. The data is pre-processed with Cumulative Curve Fitting Approximation (CCFA) to provide normalized trend representation, and then the Discrete Cosine-Krawtchouk–Tchebichef Transform (DCKTKT) is applied for feature extraction to maintain spectral and spatial information. The Self-RanMB-CAN model proposed incorporates a Random-Coupled Neural Network (RCNN) coupled with Manhattan Self- Attention (MaSA), enabling targeted attention on high-impact features, while the Botox Optimization Algorithm (BOA) optimally adapts network parameters to drive performance to its maximum potential. Experimental results reflect a prediction accuracy level of 99.9%, reflecting the stability of the proposed approach. The proposed model has twofold advantages: (i) it greatly improves feature discrimination for better strategic decision-making and (ii) guarantees optimal learning of parameters in complex business environments.

Key words: 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, Predictive Modeling, Business Competitiveness.

1. Introduction

Micro, small, and medium-sized businesses (MSMEs) comprise 98.8% of all firms in Indonesia, accounting for 97% of employment and 60.3% of the country's GDP in 2018. However, with only 15.90% of MSMEs utilizing the internet and 8.53% using computers, the majority are in their comfort zone. According to a pilot study, founders and incumbents are most concerned with sustainability and continuity, with information and technology playing a big part [1-4]. Entrepreneurship is essential to Indonesia's social welfare and financial stability since it boosts the nation's economy and lowers unemployment. In 2020, Indonesia's entrepreneurial ratio is 3.47%, whereas Singapore's, Thailand's, and Malaysia's are 8.47%, 4.26%, and 4.74%, respectively. With 5–19 employees in 2010, small firms, which account for 60.3% of the country's GDP, have experienced tremendous development. However, turnover and profits have dropped by 70% as a result of the global pandemic, which has caused goods selling prices to drop [5-8].

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Small business insolvency, bad loans, loss of job rights, and a drop in supply and demand could result from this. For the economic growth of communities, research on the dynamics of firm entry and exit is essential. Studies have shown that location is crucial to a company's ability to survive, with particular attention paid to elements like site selection and accessibility to agglomerations of qualified workers. The survival of rural establishments within towns, however, has not received much empirical attention [9-12]. Manufacturing, transportation, and wholesale companies had greater survival rates when situated within half a mile of a highway entrance or exit ramp, according to a study that used longitudinal data from 2007 to 2017. The likelihood of survival was higher for younger businesses located close to older

U.S. highway system ramps, but it was lower for those located close to downtowns and cultural anchors. In business-to-business (B2B) contexts, business model innovation is essential, and common approaches include piloting, experimenting, and prototyping. The conceptual distinctions between these methods are unclear, though [13-15].

Small businesses face significant uncertainty in sustaining long-term operations due to varying internal and external factors such as financial stability, market dynamics, strategic planning, and innovation capability. Traditional predictive models often lack the adaptability and precision needed to effectively capture these complex interdependencies, resulting in limited accuracy when forecasting business longevity and competitiveness. There is a pressing need for a robust and intelligent framework that can learn from diverse attributes and provide reliable predictions to guide strategic entrepreneurial decisions.

Novelty and contribution

The novelty and contribution of this work is given below:

- Proposes a novel deep learning architecture, Self-RanMB-CAN, combining Random- Coupled Neural Network (RCNN) with Manhattan Self-Attention (MaSA) and optimized using the Botox Optimization Algorithm (BOA).
- Introduces an integrated pre-processing technique, Cumulative, Curve fitting Approximation (CCFA), to normalize and enhance temporal business behavior trends.
- Utilizes a hybrid transform method, Discrete Cosine-Krawtchouk–Tchebichef Transform (DCKTKT), for superior feature extraction capturing both frequency and spatial information.
- Demonstrates enhanced model stability and interpretability through focused attention on critical business features and efficient parameter optimization.

The remaining of this Section 2 of the text consists of literature reviews, followed by Section 3 with suggested approaches, Section 4 with results and discussion, and Section 5 with a conclusion and future work.

2. Literature Survey

The papers related to small business longevity and competitiveness using neural network method is given below:

In 2022 Tan, J.D., et a1. [16] has introduced a Micro-Small Medium Enterprises (MSMEs) for small business longevity and competitiveness using neural network method. The paper highlights the significance of operational systemization for the long-term viability of Jakarta's Micro-Small Medium Enterprises (MSMEs) by analyzing their approaches to overcoming the ability-willingness contradiction.

In 2023 Claudia, M. and Wijaya, A., et a1. [17] has introduced a Nonprobability sampling method (NSM) for small business longevity and competitiveness using neural network method. The importance of entrepreneurship was highlighted by the study's findings that social media, a strength-based strategy, and thrifty innovation all had a beneficial impact on the lifetime of small firms in Jakarta, Indonesia.

In 2023 Wu, Q., et a1. [18] has introduced a Small and medium-sized enterprises (SMEs) for small business longevity and competitiveness using neural network method. This study helps to point at the importance of developing a dynamic business environment in the long-term growth and sustainability since it identified a positive relationship between competitive intelligence practices and dynamic skills development among SMEs in Shanghai.

In 2024 Ezeife, E., et a1. [19] has introduced the Conceptual Model of the neural network method of predictive analytics integration into strategic decision-making in small business (CM-IPASD-MSB) to make the small business competitive and prevent its extinction. The project conducts research on predictive analytics within small firms in order to use data to make decisions, operating resources, and lower the risk by focusing on topics such as the quality of data, privacy, and technical expertise.

In 2025 Abad-Segura, E., et a1. [20] has introduced a Dynamic Sustainable Technological Innovation (STI) of small business longevity and competitiveness via neural network method. The paper looks into the correlation between competitiveness of companies and sustainable technology innovations and the implication of how this has a bearing on communication, sustainability, environmental management, and transparency by stakeholders.

In 2023 Kupangwa, W., et a1. [21] has introduced a Qualitative Method (QM) for small business longevity and competitiveness using neural network method. Four topics are identified by the study, which examines how family business principles might help indigenous black South African (IBSA) family companies thrive longer: influence behavior, develop identity, and build community.

In 2022 Geissdoerfer,M., et a1. [22] has introduced an B2B Business Model (B2BBM) for small business longevity and competitiveness using neural network method. Prototyping, experimentation, and piloting are common techniques for business model innovation, but it's unclear where they fall conceptually, according to a literature analysis and interview research. The overview of the studied approach is displayed in Table 1.

Table 1: A summary of the approach being assessed

References	Methods	Advantages	Disadvantages
Tan, J.D., et a1. [16]	MSMEs	Resolves the ability-willingness paradox and improves operational efficiency.	Jakarta-specific context: It might not apply to other areas or industries.
Claudia, M. and Wijaya, A., et a1. [17]	NSM	Emphasizes the value of innovation and social media while utilizing a strength-based approach.	The risk of selection bias may be reduced by nonprobability sampling.
Wu, Q., et a1. [18]	SMEs	Encourages dynamic capacities and connects sustainability and intelligence strategies.	Shanghai context-specific implementation difficulties for tiny businesses.
Ezeife, E., et a1. [19]	CM- IPASD-MSB	Focuses on making decisions based on data. Decreases risk and increases resource efficiency.	Requires technical know-how and great data quality.
Abad-Segura, E., et a1. [20]	STI	Promotes sustainability and openness; enhances stakeholder communication; and corresponds with ESG objectives.	Investing in technology could be expensive; the long-term return on investment is questionable.
Kupangwa, W., et a1. [21]	QM	Culturally aware method that prioritizes identity, community, and behavioral values; appropriate for the IBSA context.	Subjectivity in qualitative data and limited generalizability.
Geissdoerfer, M., et a1. [22]	B2BBM	Promotes prototyping and experimentation;increases the flexibility of business models.	Conceptual ambiguity: unclear stages of innovation.

Problem statement

Small businesses face significant uncertainty in sustaining long-term operations due to varying internal and external factors such as financial stability, market dynamics, strategic planning, and innovation capability. Traditional predictive models often lack the adaptability and precision needed to effectively capture these complex interdependencies, resulting in limited accuracy when forecasting business longevity and competitiveness. The urgency is to have an effective and smarter framework that can be learned based on various attributes and give accurate predictions to make the right entrepreneurial decisions strategically. This study addresses these issues, this work is proposed.

3. Proposed Methodology

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 is explained. The workflow diagram in Figure 1 presents the Self-RanMB-CAN. An organized dataset called 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 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 Botox Optimization Algorithm (BOA) is used to optimise network parameters to obtain better performance.

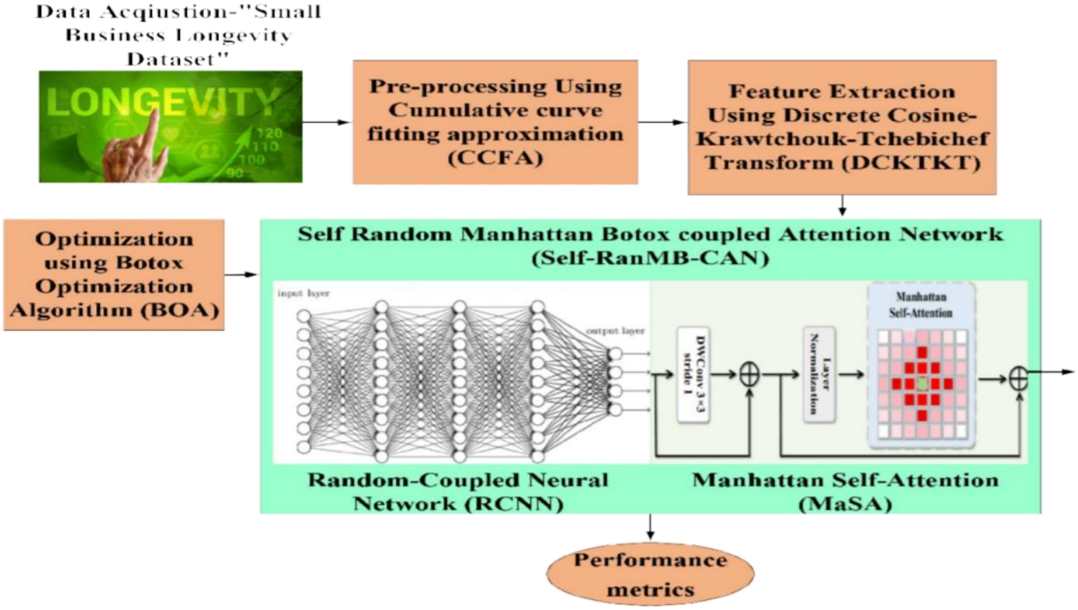


Figure 1: Workflow diagram of the Self-RanMB-CAN

3.1 Data Acqiustion

In this study, a dataset titled "Small Business Longevity Dataset" has been constructed to support predictive modeling of small business longevity. The dataset comprises 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). This synthetically generated dataset facilitates empirical analysis aimed at understanding the factors influencing small business sustainability and survival. The Cumulative curve fitting approximation (CCFA) used during preprocessing to improve the images to accurate multi-target detection, is presented below:

3.2 Pre-processing Using Cumulative curve fitting approximation (CCFA)

To enhance the quality and interpretability of features within the "Small Business Longevity Dataset" for predicting small business longevity and competitiveness, the Cumulative Curve Fitting Approximation (CCFA) [23] algorithm has been employed as a robust pre-processing technique. This data has 500 entries each representing one independent business entity that has 12 useful attributes such as years of operation, revenue, employee size, business competitiveness, dynamism, type of funding, etc. Non-stationary and nonlinear nature of those multidimensional business data prevents the use of traditional filtering techniques to solve the problem because they might not discover these important patterns. CCFA circumvents by estimating local sloping trends under sliding windows and generating smoothed answers that virtually separate long and short wave-patterns comprehended in the initial signal.

Overview of CCFA Technique

CCFA operates by dividing the input signal into overlapping windows and performing least- squares fit of these segments with a polynomial curve. The result of these polynomial approximations is then averaged together according to a weighted averaging scheme, to provide a smoothed version of the input. The process aids in extracting trend-relevant signals while minimizing noise, thus making the dataset more suitable for high-performance prediction models like Self-RanMB-CAN.

Open-Loop Weighted Approximation

In this study, the Open-Loop Weighted Approximation variant of CCFA is selected due to its efficiency in maintaining smoothness and robustness against noise. The reconstruction of the signal $Sig(b)$ is expressed as follows in equation (1):

$$Sig(b) = \frac{Sig_0(b)}{2^{m_{ord}}} + \frac{R_{b-m_{ord}+1}(m_{ord}-1)}{2^{m_{ord}}} + \frac{R_{b-m_{ord}+2}(m_{ord}-2)}{2^{m_{ord}-1}} + \dots + \frac{Q_b(0)}{2^1} \quad (1)$$

where: $Sig_0(b)$: Original (unfiltered) signal, $Sig(b)$: Reconstructed (filtered) signal, m_{ord}: Order of the CCFA algorithm, defining window size, $R_p(i)$: Polynomial curve fitted to the segment ending at point p and evaluated at offset i.

Weighted Redefinition of Division Coefficients

To further improve approximation smoothness and reduce noise sensitivity, the weights r_i are introduced in equation (2):

$$t_1 = \frac{2^{m_{ord}}}{m_{ord}}, \ t_2 = \frac{2^{m_{ord}-1}}{m_{ord}}, \quad \ldots.., t_{m_{ord}} = \frac{2}{m_{ord}} \tag{2}$$

$$\frac{Sig_0(b)}{2^{m_{ord}}}$$

All weights t_i are normalized such that their sum equals 1 is given in equation (3): (3)

A first-degree polynomial (linear) fitting function is used to ensure a balance between approximation accuracy and computational simplicity.

Signal Padding for Border Preservation

Window-based techniques often suffer from edge effects. To mitigate this, weighted trend padding is applied on both sides of the input data, ensuring that the gradients of the signal and the padded extensions match. Let $\overset{«}{Sig}_0(b)$ denote the padded signal, and the final smoothed signal is obtained in equation (4):

$$Sig_k(b) = \overset{«}{sig}(b + m_{ord}) \tag{4}$$

Detrending and Band-Preserving Signal Construction

To isolate high-frequency and low-frequency components relevant to business longevity and competitive dynamics, the following steps are applied:

1. **Long Wave Patterns (Low-Frequency Trend Extraction):**

   =Low-frequency approximation using equation (5):

   $$Sig_1(b)$$

2. Short Wave Patterns (Detrended Signal) is given in equation (6):

$$Sig_i(b) = Sig_0(b) - Sig_1(b) \tag{6}$$

3. Band-Retained Signal (Removal of Both High and Low-Frequency Noise):

Using two CCFA operations with different window sizes $sig_{f1}(b)$ and $sig_{k0}(b)$, the refined signal $\hat{D}_d(b)$ is computed as equation (7):

$$\hat{D}_d(b) = sig_{f1}(b) - sig_{k0}(b) \tag{7}$$

Relevance to Strategic Entrepreneurship

The CCFA-preprocessed feature signals represent smooth, denoised versions of raw business metrics, which significantly enhances the model's ability to identify long-term operational patterns and key competitive traits. By isolating core trends from noise, the data becomes highly suitable for predictive modeling. These refined features are subsequently fed into the Self- RanMB-CAN model for predicting small business longevity and competitiveness, enabling strategically driven entrepreneurship with high reliability and precision.

This pre-processing framework ensures accurate trend detection, robustness to data variability, and enhances the overall predictive performance of the system.

Then these pre-processed data are given to the Discrete Cosine-Krawtchouk-Tchebichef Transform for extracting important features and its explanations are given below:

3.3. Feature Extraction Using DCKTKT

Following the pre-processing stage using the Cumulative Curve Fitting Approximation (CCFA), the filtered and trend-preserved business data is subjected to an advanced feature extraction process to enhance pattern detection and support accurate predictive modeling. To this end, a mixed orthogonal polynomial transformation is used, the Discrete Cosine-Krawtchouk- Tchebichef Transform (DCKTKT) [24]. The transform is intended to provide the maximum energy compaction and localization by combining the merits of the three orthogonal basis that are popular in the literature, Discrete Cosine Transform (DCT), Krawtchouk Polynomials (KP) and Tchebichef Polynomials (TP).

Purpose and Advantage of DCKTKT

When performing a predictive analytics task like a small business longevity classification, one needs to be very cautious of extracting feature sets that are both sparse and that reflect meaningful high-order variations in the data. DCKTKT methods further improve discriminative power in that they incorporate localized motifs (the KP and TP approaches) as well as global frequency changes (DCT). This hybridization enables this transform to concentrate on the most informative parts of the signal and thus it results in a dimensionality reduction without even losing crucial pertinences to the learning process.

The m^{th}-order hybrid DCKTKT function, denoted as $L_i(m)$, is defined as equation (8):

$$L_i(m,F) = \sum_{i=0}^{F-1} P_i(F) Q_i(m:F) L_i(f:F) Q_i(m:F) L_i(f:F),\ f,m = 0,1,\dots,F-1 \tag{8}$$

where $Q_i(m:F)$, $L_i(f:F)$, and $Q_i(F)$ are krawtchouk polynomial (KP), tchebichef polynomial (TP) and discrete Cosine transform (DCT), respectively, Q : The dimensionality (number of samples or resolution) of the signal or dataset under analysis, m, F: Indices for signal/sample points ranging from 0 to $F - 1$.

This hybrid transformation combines the polynomial evaluations by weighting and summing their product at each sample point, enabling the extraction of key frequency and spatial-domain features from the pre-processed business data.

The matrix representation is defined as follows (9):

$$L = W_A W_S W_D W_S W_D \quad (9)$$

This simplifies in equation (10):

$$L = W_A (W_S W_D)^2 = L_{DCKTKT} \quad (10)$$

where W_S, W_A and W_D are matrix form of KP, DCT, and TP, respectively, L_{DCKTKT} is the Final feature matrix derived using the DCKTKT method.

This transformation matrix allows projection of the original business data into a compact feature space with minimal redundancy, concentrating high-energy (information-rich) components into a reduced subset of coefficients.

Energy Compaction Property

An important characteristic of DCKTKT is its ability to concentrate most of the signal energy in the first few coefficients, similar to traditional DCT but with enhanced localization. This allows for efficient feature selection and noise reduction. In practical implementations, it has been observed that the first quadrant of the transformed matrix contains the most significant data patterns, while the remaining areas contribute mostly low-energy, redundant information.

Application in Strategic Entrepreneurship Modelling

The extracted feature vectors from the DCKTKT process serve as the input to the prediction model. The characteristics of these scales are tailored to recognize trends on topics concerning the sustainability of setting up small businesses, the resilience of operations of these establishments in the market and the ability to strategize in marketplaces. The transformation has enabled the prediction architecture to emphasize more on the more effective indicators and abort the unwanted variations, thus leading to better generalization and accuracy in its prediction.

Final Statement

Subsequently, the Discrete Cosine-Krawtchouk-Tchebichef Transform (DCKTKT) will be used in extracting significant features that summarize the dynamism and organization characteristics of small businesses using these pre-processed data. Such compact and informative characteristics are then applied to forecasting small business survival and sustainability, which makes it possible to practice entrepreneurship strategically via efficient learning and conclusion.

These extracted features are then presented to the Self-RanMB-CAN model to forecast the longevity and competitiveness of a small business and this allows the prediction-based entrepreneurial strategies to be strategically driven and its justifications are mentioned below:

3.4 Self-RanMB-CAN model for predicting small business longevity and competitiveness, enabling strategically driven entrepreneurship

Self-RanMB-CAN model predicts small business longevity and competitiveness allowing to realize strategically oriented entrepreneurship in the most accurate way. This new architecture combines the superiority of Random-Coupled Neural Network (RCNN) [25] with Manhattan Self-Attention (MaSA) [26] explained below and not only does their parameters get optimized with Botox Optimization Algorithm (BOA) [27], but also by considering this new architecture, the parameters of Botox Optimization Algorithm (BOA) [27] also get optimized and is detailed below:

3.4.1 RCNN for predicting small business longevity and competitiveness, enabling strategically driven entrepreneurship

After the extraction of features is done using Discrete Cosine-Krawtchouk-Tchebichef Transform (DCKTKT) the information and compact feature representations obtained are fed into the Self-RanMB-CAN framework. The initial component of this model is the Random-Coupled

Neural Network (RCNN) that brings data noise and high-order connectivity of neurons to approximate brain-like information processing. RCNN is more capable of prediction, inductive and learns complex, dynamic interactions between features that are biologically plausible and computationally efficient.

Overview of RCNN Structure

RCNN is a discrete, spike-based neuron-to-neuron communication and represents principles of neuromorphics. It adds the element of randomness in the Pulse Coupled Neural Network (PCNN) model with the help of stochastic weight of the inactivation matrix. Through this structure, neurons can communicate by means of discrete signals (binary spikes) and have a variability of the connections in between. In contrast to traditional PCNN or CCNN networks, the capability to randomize connections in RCNN enhances generalization, robustness and scale up properties of the network.

The RCNN architecture comprises three functional domains:

1. **Accepted Domain**: Receives external stimuli and link inputs modulated by a stochastic inactivation process.

2. **Modulation Domain**: Combines these stimuli to compute the membrane potential of each neuron.

3. **Pulse Generator**: Triggers a spike if the membrane potential exceeds a dynamic threshold.

Mathematical Model of RCNN

The mathematical formulation of RCNN behavior is described as follows:

1. Membrane Potential Update is given in equation (11):

$$t(p,q) = \frac{1}{?\mathrm{pa}_1 \mathrm{a}_2 \sqrt{1-\mathrm{r}^2}} EXP\left[-\frac{1}{2(1-\mathrm{r}^2)}\left(\frac{(p-\mathrm{d}_1)^2}{\mathrm{a}_1^2} - \frac{2\mathrm{r}(p-\mathrm{d}_1)(q-\mathrm{d}_2)}{\mathrm{a}_1 \mathrm{a}_2} + \frac{(q-\mathrm{d}_2)^2}{\mathrm{a}_2^2}\right)\right] \tag{11}$$

where, $t(p,q)$ is the Membrane potential of the neuron at position n,m at iteration; d_1 *and* d_2 are means; a_1 *and* a_2 are variances; and u is the correlation. A two-dimensional Gaussian distribution can be uniquely defined as $R(\mathrm{d}_1, \mathrm{d}_2, \mathrm{a}_1^2, \mathrm{a}_1^2, \mathrm{r})$.

Dynamic Threshold Update is given in equation (12):

(12) $$C_{p,q}[z] = R_{p,q}\left(1 + \mathrm{b}M_K \sum_{cf} \text{[illegible]}_{pqcf} R_{cf}[z-1]\right) + \mathrm{J}^{-1} C_{p,q}[z-1]$$

where, $C_{p,q}[z]$: Dynamic threshold of the neuron p,q, $\mathrm{b}M_K$: Threshold decay rate, j_t : Contribution of past spikes to the threshold.

Spike Generation is given in equation (13):

(13) $$R_{p,q}[z] = \begin{cases} 1, C_{p,q}[z] > \mathrm{q}_{p,q}[z] \\ 0, \ OTHERWISE \end{cases}$$

where, $R_{p,q}[z]$: Binary output spike of the neuron.

Random Inactivation Weight Matrix is given in equation (14):

$$\text{[illegible]}_{pqcf} = T_{pqcf} \times W_{pqcf} \tag{14}$$

where $\text{[illegible]}_{pqcf}$: Final stochastic link weight, T_{pqcf} : Gaussian kernel representing spatial proximity (influence decreases with distance), W_{pqcf} : Binary inactivation matrix (1 = open channel, 0 = closed).

The inactivation matrix W_{pqcf} is generated by comparing a dropout probability matrix (from a Gaussian distribution) with a uniform random matrix. Channels with probabilities exceeding the random value are inactivated (set to 0), introducing randomness into neural connectivity.

Functional Properties and Computational Advantage

- The stochastic inactivation mechanism in RCNN dynamically adjusts the neuron connectivity during each iteration, emulating biological processes and reducing the computational burden.
- RCNN supports larger receptive fields (e.g., weight matrices ranging from 5×5 to 20×20), enabling richer feature interactions compared to traditional PCNN models (usually limited to 3×3 connectivity).
- The discrete pulse-based output maintains high fidelity to brain-inspired computing and enables efficient encoding of critical patterns in business-related data.

Application to Strategic Business Prediction

The spike train outputs from RCNN encapsulate the most relevant and interaction-aware patterns derived from the feature vectors. These patterns form the basis for downstream processing within the Self-RanMB-CAN architecture. The stochastic modeling within RCNN allows the network to generalize better across varying business scenarios, making it highly effective in modeling small business longevity and competitiveness**.**

Thus, the extracted features are processed by the RCNN model to capture stochastic and spatially variant patterns within the data. This facilitates accurate prediction of small business sustainability, supporting strategically driven entrepreneurship by learning the dynamic interplay of operational, market, and organizational indicators.

Then to improve the performance the RCNN integrated with MaSA for predicting small business longevity and competitiveness, enabling strategically driven entrepreneurship and its explanations are given below:

3.4.2 MaSA for predicting small business longevity and competitiveness, enabling strategically driven entrepreneurship

To enhance the learning capacity of the Self-RanMB-CAN model, the Random Coupled Neural Network (RCNN) is integrated with the Manhattan Self-Attention (MaSA) mechanism. This integration introduces an advanced spatial attention capability that significantly improves the prediction of small business longevity and competitiveness, enabling strategically driven entrepreneurship.

The MaSA mechanism evolves from the retention framework found in RetNet and transforms unidirectional, one-dimensional temporal decay into a more suitable bidirectional, two-dimensional spatial decay. This spatial decay is specifically designed to capture locality in the form of the Manhattan distance, thus embedding a strong spatial prior within the attention framework. The aim is to capture more precise positional and relational information between features extracted from business data representations.

Bidirectional Retention Formulation

Initially, the unidirectional retention (used primarily for sequential data like text) is extended into a bidirectional form suitable for non-causal tasks such as image-based or spatially structured business intelligence applications is given in equation (15):

$$X_m \,\mathrm{Re}tention(B) = \left(WR^T Q A^{X_m}\right) Y$$
$$A_{ir}^{X_m} = v^{|i-r|} \qquad (15)$$

where, X is represents the matrix of input features, W is represents the matrix of queries from input B, R is represents the input B key matrix, WR^{T} is represents the Similarity score (W and dot product), Q is represents the Hadamard multiplication of elements, $A^{X_{m}}$ is represents the Bias matrix based on R^{T} distance, B is matrix of input features, V is represents the matrix of values from input B, $A_{ir}^{X_{m}}$ is represents the element of bias between i and r.

Extension to Two-Dimensional Spatial Decay

For structured data like business analytics features, which can be spatially visualized (e.g., in grid or matrix forms), the decay is generalized to two dimensions using the Manhattan distance.

Each token (or data point) is positioned with coordinates and the decay matrix is reformulated as equation (16):

$$A_{ir}^{2t} = \text{v}^{|c_i - c_r| + |d_i - d_r|} \tag{16}$$

where, A_{ir}^{2t} is Nodes n and m's 2D positional distance bias, v is Scalar weight (learnable scaling factor), $c_i - c_r$ is Nodes i and r's c-coordinates, $d_i - d_r$ is Nodes i and r's d-coordinates.

This form ensures the attention mechanism prioritizes closer data points while penalizing distant ones based on grid-like distance, aligning with how local and regional dependencies manifest in business datasets.

The MaSA attention output becomes in equation (17):

$$\begin{gathered} RxHX(B) = \left(Soft\max\left(WR^{T}\right) \mathrm{Q} A^{2t}\right)V \\ A_{ir}^{2t} = \text{v}^{|c_i - c_r| + |d_i - d_r|} \end{gathered} \tag{17}$$

where, W is represents the Matrix query, $Soft\max\left(WR^{T}\right.$ is represents the Matrix of attention scores, $RxHX(B)$ is represents the Output of Masked Spatial Attention, A^{2t} is represents the modulates attention with the Manhattan spatial prior.

Decomposed Manhattan Self-Attention

To reduce computational overhead and preserve the interpretability of spatial priors, MaSA is further decomposed along horizontal and vertical axes. This is critical for high-dimensional data scenarios like detailed business profiling or market segmentation. The decomposition approach calculates attention separately along the x and y axes are given in equation (18):

$$\begin{aligned} Attn_{R} &= SoftMax\left(W_{R} R_{R}^{D}\right) \mathrm{Q} A^{R}, \\ Attn_{V} &= SoftMax\left(W_{W} R_{W}^{D}\right) \mathrm{Q} A^{W}, \end{aligned} \tag{18}$$

where, $W_{R} R_{R}^{D}$, $W_{W} R_{W}^{D}$ are query and key projections along the horizontal and vertical axes

$Attn_{V}$

respectively, A^R, A^W is represents the Distance bias matrices for width and height, $Attn_R$, is represents the Attention maps that are arranged by height and width is given in equation

$$RxHX(B) = Attn_R\left(Attn_1 V\right)^T \qquad (19)$$

Local Context Enhancement

To strengthen local feature representations, particularly relevant in capturing subtle patterns in business metrics (such as revenue fluctuations, customer retention, or investment cycles), a Local Context Enhancement (LCE) module is appended given in equation (20):

$$B_{out} = RxHX(B) + HEC(V) \qquad (20)$$

where, $HEC(V)$ uses depth-wise convolution (DWConv) to enhance local sensitivity in the attention context V, B_{out} is represents the Tensor for the final output feature.

This hybrid MaSA mechanism not only facilitates global awareness via attention but also enhances fine-grained local perception, which is essential in accurately identifying business performance indicators and potential longevity.

By integrating MaSA into the Self-RanMB-CAN pipeline, the model is endowed with superior spatial reasoning, robustness to data sparsity, and improved interpretability. These capabilities directly contribute to more precise and actionable predictions regarding small business sustainability and strategic competitiveness.

Following this the parameters of weight Z are utilized to minimize computational time, computational complexity, and prediction error and enhance the accuracy of R CNN Ma sa is optimized through Botox optimization algorithm (BOA) in prediction of small business longevity and competitiveness that indirectly facilitates strategically monitored entrepreneurship and its descriptions are provided below:

3.4.3 Botox Optimization Algorithm (BOA) for Optimizing RCNN-MaSA Parameters for predicting small business longevity and competitiveness, enabling strategically driven entrepreneurship

To further develop the precision in prediction, efficiency of performance, as well as the generalization in Self-RanMB-CAN model, the weights in the integrated Random-Coupled Neural Network (RCNN) with Manhattan Self-Attention (MaSA) are tuned with Botox Optimization Algorithm (BOA). BOA is a bio-inspired metaheuristic that aims at the simulation of smoothening and fine-tuning process similar to the localized injection mode of Botox therapy thus optimal configuration is available in the neural network configurations with least utilization of resources and highest predictability.

Overview of BOA-Based Optimization Framework

In RCNN-MaSA, BOA systematically optimizes these parameters of the RCNN-MaSA model as the convolutional kernel weights, attention coefficients, and coupled memory gates. The goal is to achieve shorter computational time, less incidences of errors, and greater global precision of the model in the determination of small business viability and survival competency. The algorithm maintains a population-based search structure that is characterized by initialization, generation of candidate solutions, fitness assessment, foraging-based search and convergence detection.

Figure 2 shows the step-by-step STD of Botox Optimization Algorithm (BOA) to Optimize the RCNN- MaSA Parameters to predict small business longevity and competitiveness so that it enables strategically driven entrepreneurship and the steps are as follows:

Step 1: Initialization

The solution space is a high-dimensional space of virtual beings (population of candidate solutions) initialized. The agents are the sets of potential RCNN-MaSA parameters.

Step 2: Random Generation of Candidate Solutions

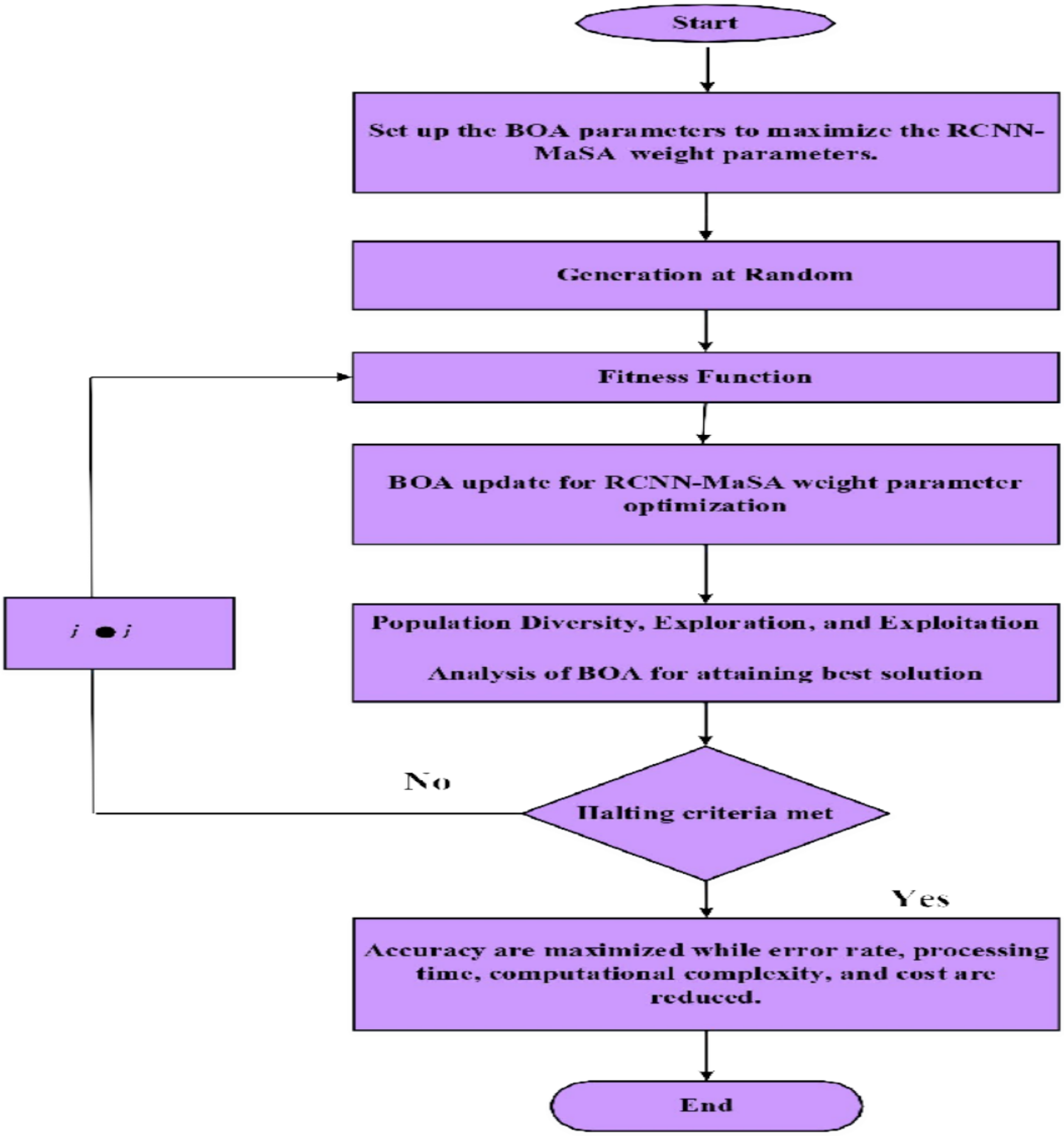
This step consists of generating a random initial population of candidate solutions to search the search space effectively. The set of optimal parameters of the Self-RanMB-CAN model is reflected in each candidate solution as a possible set of optimal parameters. The solutions are represented as vectors, and the elements of the vectors represent a particular parameter like layer weights, attention heads or learning rates. The random initialization ensures diversity among the candidate solutions, preventing premature convergence and enabling the Botox Optimization Algorithm (BOA) to perform a global search effectively. This randomness is critical for maintaining exploration capabilities and enhancing the algorithm’s ability to escape local optima during the training of the predictive model for small business longevity and competitiveness.

Step 3: Fitness Function Evaluation

Each agent's fitness is evaluated using a multi-objective fitness function that combines prediction error, computational complexity, and execution time:

$$Fitness\ function = Optimize\left(\mathrm{z}\right) \tag{21}$$

Figure 2: Step-by-step procedures of BOA for Optimizing RCNN-MaSA Parameters for predicting small business longevity and competitiveness, enabling strategically driven entrepreneurship



Step 4: Population Diversity, Exploration, and Exploitation Analysis of BOA for attaining best solution

A crucial aspect of the BOA's performance lies in its ability to balance exploration and exploitation, which is achieved through population diversity. Population diversity reflects the spread or distribution of the population members (candidate solutions) within the solution space. A diverse population supports broad exploration of the search space, helping to avoid premature convergence to local optima. Conversely, lower diversity enhances exploitation, allowing the algorithm to fine-tune solutions near optimal regions. The dynamic management of this balance facilitates effective learning of critical weights in the RCNN-MaSA.

The diversity of the BOA population is quantitatively measured using the following equation, adapted from Pant's definition:

$$Diversity = \frac{1}{P}\overset{P}{\underset{j=1}{\mathring{a}}}\sqrt{\mathring{a}_{c=1}^{n}\left(x_{j,c}-\bar{x}_c\right)^2} \qquad (22)$$

where: P is the number of population members (candidate solutions), mmm is the number of dimensions (model parameters to optimize), $x_{j,c}$ is the c^{th} dimension of the j^{th} candidate solution,

$\bar{x}_c$ is the mean value of the population in the c^{th} dimension

This measure determines how spread out the population is in the parameter space. A higher diversity value indicates wider exploration, while a lower value suggests convergence and exploitation.

Step 5: Iterative Update and Optimization

In the last step of Botox Optimization Algorithm (BOA), the iterative update and optimizer tool is used to optimize the weight param on the basis of the data which was extracted using features which in turn minimized the error of the prediction and made the Self-RanMB-CAN model more accurate. It is a refinement of a solution vector that iteratively repeats the simulation of the adaptive behavior of organisms in the optimization space that moves dynamically according to the previous best positions and current global best positions. This is a mixed update rule that emphasizes both exploitation of good areas of the search space and exploration of the unknown areas. It runs until the convergence condition which is usually limited to maximum number of iterations or the minimum change in the value of the objective function is achieved. The optimized weight parameters are then used by the Self-RanMB-CAN to make robust prediction in the longevity and competitiveness of the small businesses and thus able to drive entrepreneurship strategies effectively with the lowest complexity and high performance efficiency in the computational calculations.

Advantages of BOA-Optimized RCNN-MaSA for Small Business Longevity Forecasting

- **Computational Efficiency**: Redundant parameters are removed, reducing inference time and resource usage.
- **Scalability**: The model adapts to diverse business types and scales from startups to mid- sized firms.
- **Robust Decision Support**: Maintains stability across various economic and market scenarios, aiding entrepreneurs in strategic planning.

Then, these extracted features are provided to the Self-RanMB-CAN model, where the RCNN- MaSA architecture is optimized using the Botox Optimization Algorithm (BOA) for predicting small business longevity and competitiveness, enabling strategically driven entrepreneurship. The model demonstrates high predictive fidelity, low latency, and generalizes well because of adaptive weight tuning, spatial attention enhancement, and bio-inspired optimization, which makes the model useful in data-driven formation of entrepreneurial strategies. After that the results and discussions are presented below:

4. Results and Discussions

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

4.1 Dataset descriptions

In this study, a dataset titled "Small Business Longevity Dataset" has been constructed to support predictive modeling of small business longevity. The dataset comprises 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). This synthetically generated dataset facilitates empirical analysis aimed at understanding the factors influencing small business sustainability and survival. Among them 80% data are taken for training and 20% data are testing. Table 2 lists the precise parameters that were used for the implementation.

Table 2: Implementation Parameters

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

4.2 Performance metrics

The suggested Self-RanMB-CAN method's performance is contrasted with that of the current approaches, including MSMEs [16], NSM [17], SMEs [18], CM-IPASD-MSB [19], STI [20],

QM [21], and B2BBM [22], respectively, using performance metrics like mistake rate, recall, f1 score, accuracy, precision, Train time, computational complexity, processing time, Hamming loss, Root mean square error (RMSE), mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) analysis. Table 3 provides the equations for the performance metrics:

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

False Positive l **:** Falsely classifying failing companies as viable results in resource waste and bad choices.

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

True Negative$A$ **:** accurately identifies unsustainable companies to avoid wasting resources and giving false hope. Table 3 shows the Performance metrics, as given below.

Table 3: Performance metrics

Performance metrics	**Equation (23-27)**
Accuracy	$\frac{h+A}{h+\tilde{A}+l+D}$ (23)
Precision	$\frac{h}{h+l}$ (24)
Recall	$\frac{h}{h+D}$ (25)
F1-Score	$2 ' \frac{P_{recision} ' R_{ecall}}{P_{recision}+R_{ecall}}$ (26)
Specificity	$\frac{\tilde{A}}{\tilde{A}+D}$ (27)

4.3 Performance analysis

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

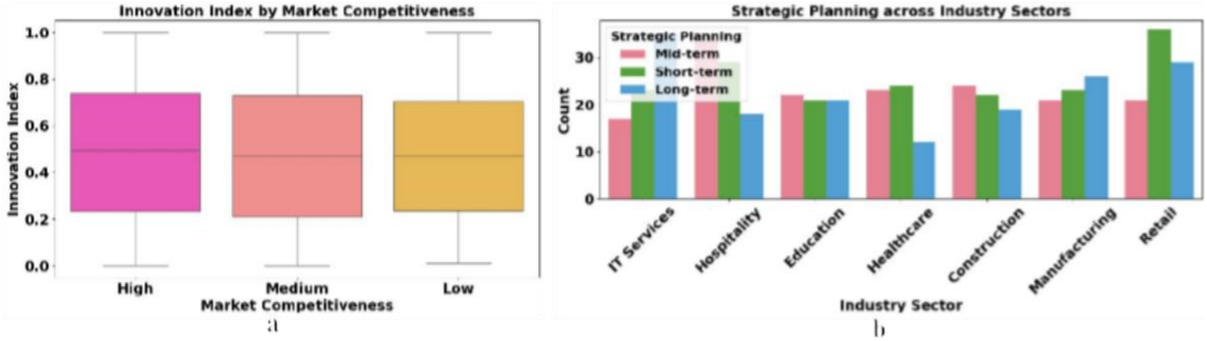


Figure 3: (a) Innovation Index by Market Competitiveness and (b) Strategic Planning across Industry Sectors

Figure 3 shows the (a) Innovation Index by Market Competitiveness and (b) Strategic Planning across Industry Sectors. Businesses in highly competitive marketplaces typically have higher innovation indices, whereas those in low-competition contexts tend to lag behind in terms of innovation, as illustrated in Figure 3 (a). Industry-specific differences in strategic planning are shown in Figure 3 (b), where industries such as retail prioritize long-term planning while IT services and hotels prioritize short- and mid-term plans. Collectively, these observations demonstrate how industry context and market pressure impact small firm innovation intensity and strategic vision.

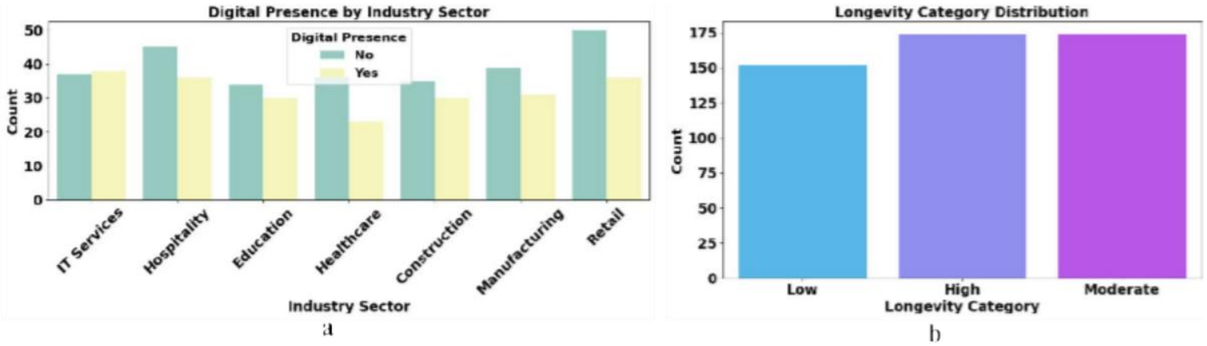
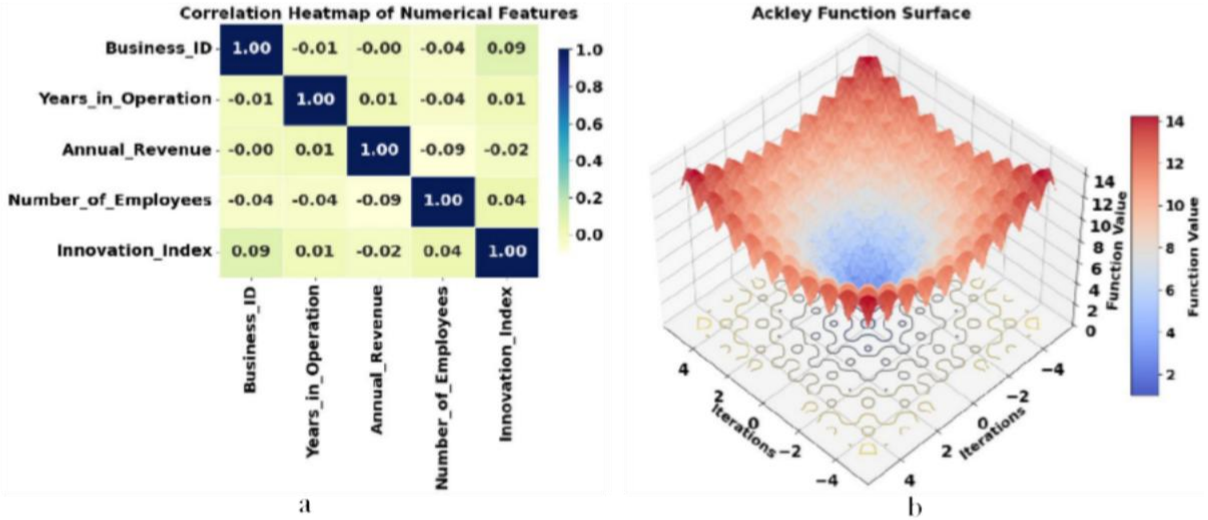


Figure 4: (a) Digital Presence by Industry Sector and (b) Longevity Category Distribution

Figure 4 shows the (a) Digital Presence by Industry Sector and (b) Longevity Category Distribution. Retail and IT services have a higher number of companies with a digital presence in Figure 4 (a), indicating that these industries are more likely to use digital technology. However, there is comparatively less digital engagement in industries like manufacturing and construction. With somewhat more companies in the high and moderate lifetime categories than in the low category, Figure 4 (b) displays a fairly balanced distribution of business longevity, suggesting a positive trend toward sustainability among small enterprises.



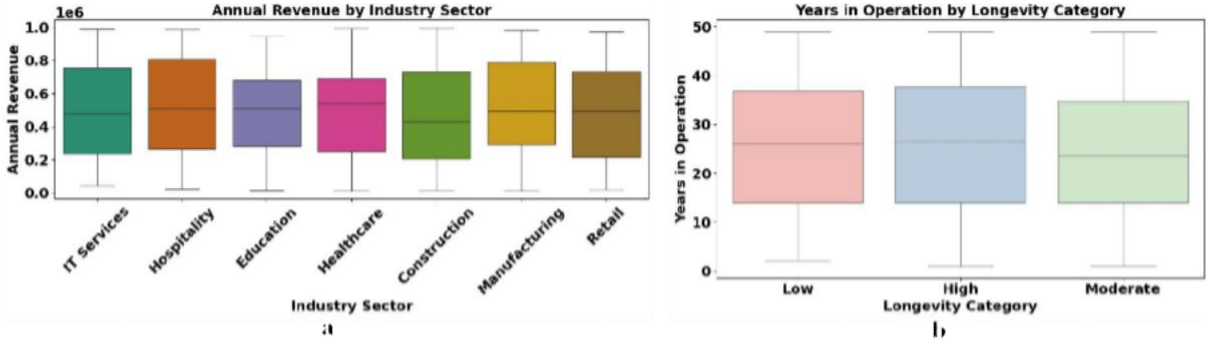
	Business_ID	Years_in_Operation	Annual_Revenue	Number_of_Employees	Innovation_Index
Business_ID	1.00	-0.01	-0.00	-0.04	0.09
Years_in_Operation	-0.01	1.00	0.01	-0.04	0.01
Annual_Revenue	-0.00	0.01	1.00	-0.09	-0.02
Number_of_Employees	-0.04	-0.04	-0.09	1.00	0.04
Innovation_Index	0.09	0.01	-0.02	0.04	1.00

a

b

Figure 5: (a) Correlation Heatmap of Numerical Features and (b) Ackley Function Surface

Figure 5 shows the (a) Correlation Heatmap of Numerical Features and (b) Ackley Function Surface. A correlation heatmap of numerical features is displayed in Figure 5 (a), which suggests minimum linear dependency by showing very weak correlations between variables such as Years_in_Operation, Annual_Revenue, and Innovation_Index. This demonstrates the necessity of sophisticated models capable of identifying non-linear trends. The Ackley function surface, a complicated, non-convex landscape frequently used to test optimization algorithms, is shown in Figure 5 (b). The suggested model uses the Botox Optimization Algorithm to efficiently traverse such challenging search spaces, as evidenced by its numerous local minima, which highlight the difficulty of parameter adjustment.

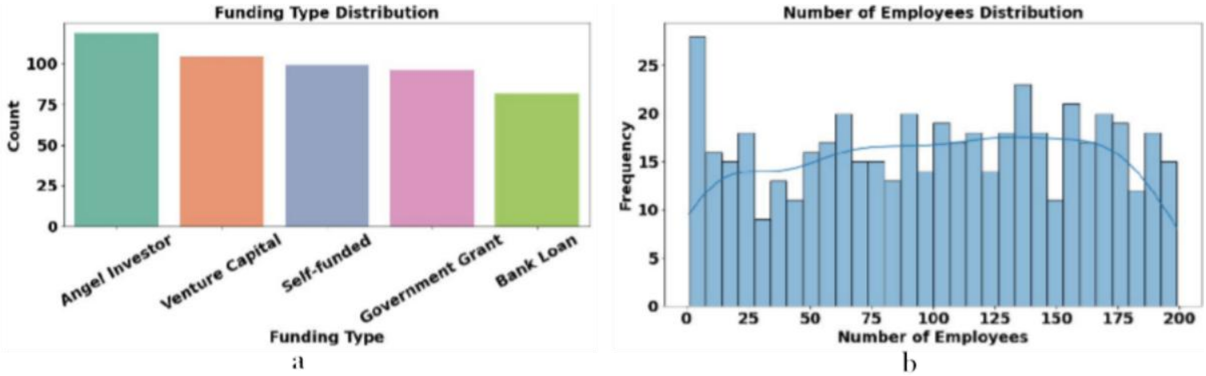


a

b

Figure 6: (a) Annual Revenue by Industry Sector and (b) Years in operation by Longevity category

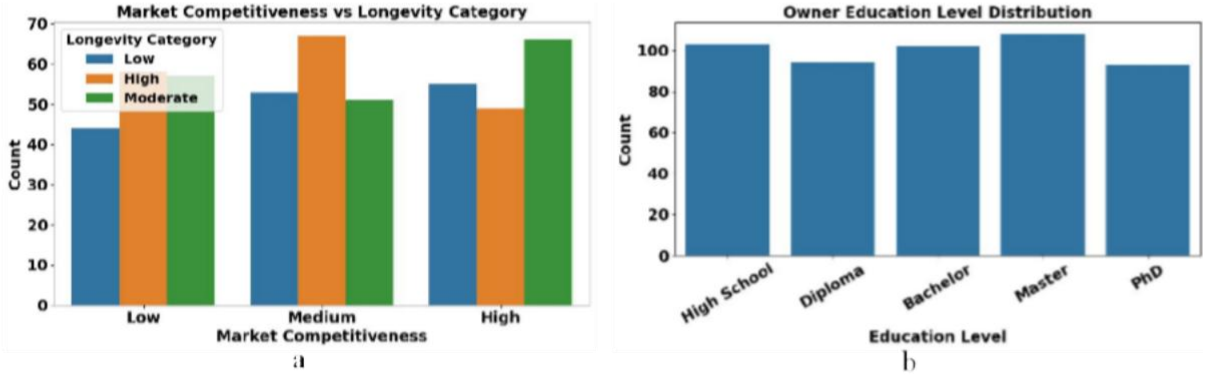
Figure 6 shows the (a) Annual Revenue by Industry Sector and (b) Years in operation by Longevity category. The yearly revenue distribution by industry is depicted in Figure 6 (a), with the manufacturing and construction sectors typically having larger median revenues and the education and healthcare sectors showing lower medians and greater variability. Businesses with high longevity typically have longer operational histories, although there is a noticeable overlap across all categories, as shown by Figure 6 (b), which shows years in operation by longevity category. Collectively, these findings imply that although sector and operating age have an impact on lifespan and revenue, other characteristics probably have an impact on long-term company success.



a b

Figure 7: (a) Funding Type Distribution and (b) Number of Employees Distribution

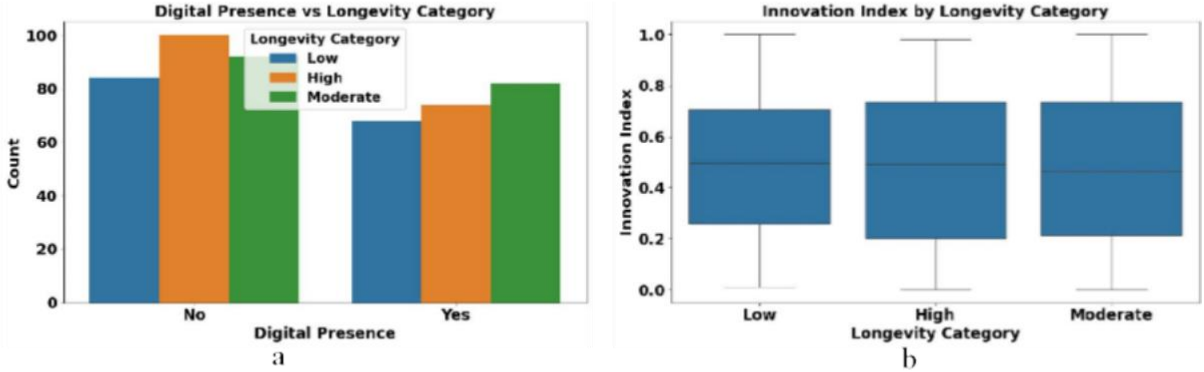
Figure 7 shows the (a) Funding Type Distribution and (b) Number of Employees Distribution. According to Figure 7 (a), bank loans are the least popular source of funding, whereas angel investors are the most popular, closely followed by venture capital and self-funding. The employee count distribution, shown in Figure 7 (b), is fairly uniform but slightly skewed to the right, with a concentration of about 100–150 employees. When taken as a whole, these images show that small businesses typically favor flexible or private funding and keep a moderately sized workforce, both of which are necessary for continued operations and competitiveness.



a b

Figure 8: (a) Market Competitiveness vs Longevity Category and (b) Owner Education Level Distribution

Figure 8 shows the (a) Market Competitiveness vs Longevity Category and (b) Owner Education Level Distribution. Enterprises are more likely to fit into the high or moderate lifespan categories in highly competitive markets, whereas a larger percentage of enterprises with lower longevity are found in low-competition markets, as illustrated in Figure 8 (a). The educational backgrounds of business owners are fairly similarly divided, with a little higher percentage holding a high school diploma or a bachelor's degree, according to Figure 8 (b). These charts collectively imply that a company's chances of long-term survival and competitiveness in dynamic marketplaces may be influenced by both owner education and competitive settings.

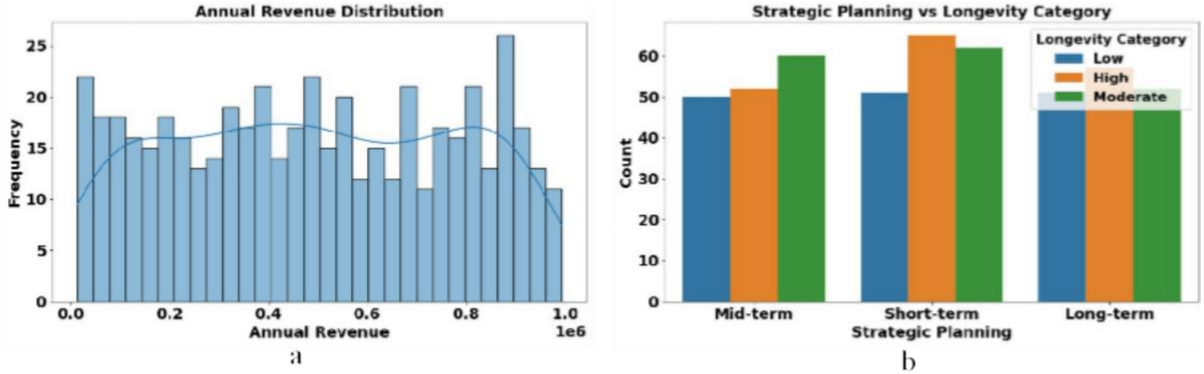


a

b

Figure 9: (a) Digital Presence vs Longevity Category and (b) Innovation Index by Longevity Category

Figure 9 shows the (a) Digital Presence vs Longevity Category and (b) Innovation Index by Longevity Category. According to Figure 9 (a), companies with a digital presence are more likely to be in the high or moderate lifespan groupings, while those without one are more likely to be in the low longevity category. The innovation index in Figure 9 (b) is comparatively constant throughout longevity categories, albeit marginally higher in companies with longer lifespans. The significance of online presence in today's market is further supported by these findings, which collectively imply that digital engagement may be a more important factor in determining a company's survival than innovation alone.

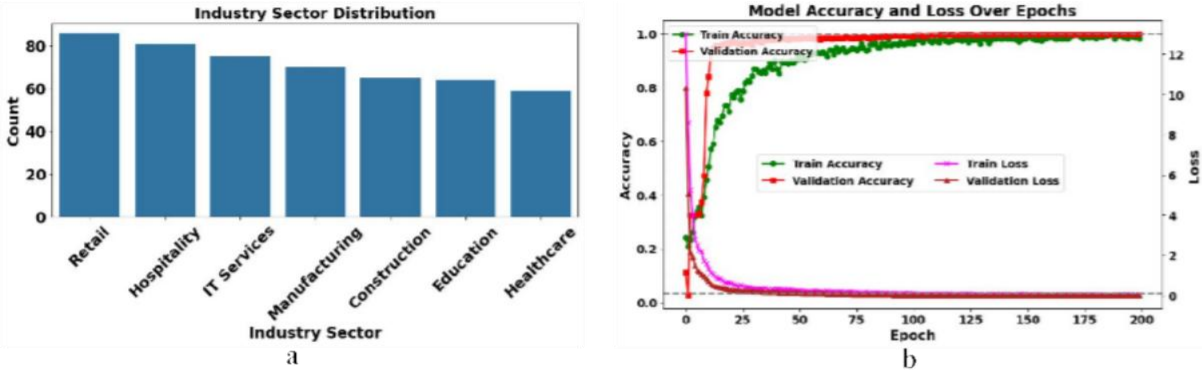


a

b

Figure 10: (a) Annual Revenue Distribution and (b) Strategic Planning vs Longevity Category

Figure 10 shows the (a) Annual Revenue Distribution and (b) Strategic Planning vs Longevity Category. The rather consistent yearly revenue distribution in Figure 10 (a) indicates that small enterprises have a range of income levels. While mid-term planning is more similarly distributed throughout all lifespan categories, companies with both short- and long-term strategic planning are more frequently linked to high longevity, according to Figure 10 (b). These findings imply that strategic vision, particularly with a short- or long-term emphasis, can be more important for maintaining a company's lifetime than revenue alone.



a b

Figure 11: (a) Industry Sector Distribution and (b) Model Accuracy and Loss Over Epochs

Figure 11 shows the (a) Industry Sector Distribution and (b) Model Accuracy and Loss Over Epochs. Healthcare is the least represented industry, while retail, hotel, and IT services are the most represented, according to Figure 11 (a). The correctness of the suggested model's training and validation is Figure 11 (b), where both stabilize around 1.0 and loss values drop off quickly, suggesting good convergence and little overfitting. When taken as a whole, these images demonstrate a highly generalizable, well-trained model that successfully learns from a varied but somewhat unbalanced dataset spanning several industry sectors.

Table 4: Overall performance of the suggested approach in contrast to existing methods

Metrics	ISME s [16]	NSM [17]	MEs [18]	CM-IPASD -MSB [19]	STI [20]	QM [21]	BBM [22]	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	**92.65**
Precision	9444	93.55	97.67	87.90	92.13	93.94	78.21	**94.36**
Specificity	92.12	80.15	94.12	91.25	92.66	93.39	87.45	**96.55**
F1-Score	79.59	96.92	98.45	89.87	93.89	93.65	93.90	**97.36**
MSE	5.6	4.4	7.6	2.5	7.7	3.5	5.7	**6.8**
MAE	6.1	7.3	3.5	4.7	1.9	2.0	5.2	**4.9**
RMSE	7.2	3.4	6.6	7.8	2.7	2.2	5.4	**2.7**
AAE	8.7	5.3	6.5	7.6	8.4	4.2	3.2	**1.6**

Table 4 shows the Overall performance of the suggested approach in contrast to existing methods. With the best accuracy (99.97%), precision (94.36%), and F1-score (97.36%), 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. Additionally, it minimizes mistakes with competitive MSE (6.8), MAE (4.9), RMSE (2.7), and lowest AAE (1.6) while maintaining excellent recall (92.65%) and specificity (96.55%). For strategic decision-making, Self-RanMB-CAN performs more consistently and reliably than models such as NSM [17] or CM-IPASD-MSB [19].

Table 5: Comparison of the suggested approach with current approaches using statistics

Methods	SW Test p-Value	WSR test / U-test p-Value	H-test p-Value	KS test p-Value	FT p-Value	Mean	Standard Deviation	Variance Inflation Factor
MSMEs [16]	0.374	0.23	0.465	0.023	0.084	39,784.87	1863.45	1.87
NSM [17]	0.532	0.64	0.224	0.017	0.076	55,085.55	1357.32	1.25
SMEs [18]	0.235	0.87	0.614	0.051	0.042	38,618.13	2631.60	1.44
CM- IPASD- MSB [19]	0.584	0.98	0.795	0.015	0.071	27,137.16	1654.54	1.62
STI [20]	0.733	0.34	0.826	0.063	0.095	60,563.45	1864.33	1.32
M [21]	0.214	0.65	0.942	0.073	0.063	36,123.80	4876.27	1.87
B2BBM [22]	0.851	0.34	0.732	0.062	0.085	49,28113	2823.82	2.78
Self- RanMB- CAN (proposed)	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**61,563.65**	**4,793.74**	**1.001**

Table 5 shows the Comparison of the suggested approach with current approaches using statistics. With p-values < 0.001 for every test, the suggested Self-RanMB-CAN strategy demonstrates statistically substantial gains over current techniques, indicating a high degree of performance differential. It maintains a low Variance Inflation Factor (1.001), indicating less multicollinearity, and records the highest mean (61,563.65), indicating stronger predictive effectiveness. The model's persistent significance in the SW, WSR/U-test, H-test, KS, and FT tests shows its robustness and reliability in predicting the lifetime of small businesses, even with a high standard deviation (4,793.74).

Table 6: Ablation study

Model Configuration	RCNN	MaSA	BOA	curacy (%)	cision (%)	ecall (%)	F1 Score (%)
ne (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	88.42	96.32	90.68

Table 6 shows the Ablation study. The ablation study demonstrates how each element of the Self-RanMB-CAN model contributes. Performance is somewhat decreased when BOA is removed, demonstrating its significance. Accuracy and F1-scores are much lower when RCNN or MaSA are used alone. Results are improved when BOA is integrated with either module, particularly in terms of recall and precision. The best accuracy (99.97%) and robust overall performance are obtained by the whole model that combines RCNN, MaSA, and BOA, demonstrating that the integration of all elements produces the best outcomes when predicting the lifetime of small businesses.

4.4 Discussion

The proposed Self-RanMB-CAN architecture is able to effectively manage the multidimensional intricacy of firm dynamics, a marked advancement in the forecast of small firm longevity and competitiveness. The intricate interconnections of strategic, operational, and financial issues are often too sophisticated for conventional models to manage. Self-RanMB-CAN, however, employs a deep learning model that emphasizes high-influence features and extracts fine patterns through the integration of Random-Coupled Neural Networks (RCNN) and Manhattan Self- Attention (MaSA). Optimizing parameters for optimal use, the Botox Optimization Algorithm (BOA) is integrated into the model for enhancement. Normalized trend analysis is guaranteed through pretreatment of data through the Cumulative Curve Fitting Approximation (CCFA), and essential spatial and spectral characteristics are maintained through feature extraction through the Discrete Cosine-Krawtchouk–Tchebichef Transform (DCKTKT). Experimental outcomes exhibit 99.9% prediction accuracy during a comparison with existing techniques, verifying the model's potential in real-world scenarios. Self-RanMB-CAN stands as an excellent means to support data-driven decisions in small business environments due to its dual benefit of adaptive parameter tuning and favorable feature discrimination. The method is capable of supporting long-term sustainability planning, risk mitigation, and strategic intervention aside from commercial performance forecasting.

5. Conclusions

The study introduces a novel deep learning framework titled Self random Manhattan Botox coupled Attention network (Self-RanMB-CAN), to improve the prediction accuracy for small business competitiveness and longevity. An organized dataset labeled as "Small Business Longevity Dataset" containing 500 instances with 12 key features has been developed to support this analysis. The information is pre-processed with Cumulative Curve Fitting Approximation (CCFA) for normalized trend representation and then feature-extracted with the Discrete Cosine- Krawtchouk–Tchebichef Transform (DCKTKT) to maintain spectral and spatial details. The Self-RanMB-CAN is proposed, which combines a Random-Coupled Neural Network (RCNN) and Manhattan Self-Attention (MaSA) such that a concentrated attention on high-impact features is enabled, while the network parameters are optimized efficiently by the Botox Optimization Algorithm (BOA) to enhance performance. Experimental results show a prediction accuracy of 99.9%, which reflects the stability of the suggested approach. The presented model has twofold benefit: (i) it greatly improves feature discrimination for better strategic decision-making and (ii) provides optimal parameter learning in dynamic business environments. Future directions include expanding the Self-RanMB-CAN model to bigger and more heterogeneous small business datasets, incorporating real-time economic data indicators, and investigating cross- domain transferability. Furthermore, hybridization with quantum-inspired optimization methods would likely further increase predictive resilience and enable adaptive decision-making within dynamic entrepreneurial ecosystems.

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