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Enhancing Innovation Management and Venture Capital Evaluation via Advanced Deep Learning Techniques

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ABSTRACT

Innovation management involves planning, organizing, and controlling innovation within an organization, while venture capital evaluation assesses investment opportunities in startups and early-stage companies. Both fields require effective decision-making and data analysis. This study aims to enhance innovation management and venture capital evaluation by combining CNN and GRU using deep learning. The approach consists of two steps. First, the authors build a deep learning model that fuses CNN and GRU to analyze diverse data sources like text, finance, market trends, and social media sentiment. Second, they optimize the model using the gorilla troop optimization (GTO) algorithm, inspired by gorilla behavior. GTO efficiently explores the solution space to find optimal or near-optimal solutions. The authors compare the fused CNN-GRU model with traditional methods and evaluate the GTO algorithm's performance. The results demonstrate improvements in innovation management and venture capital evaluation.

KEYWORDS

CNN, Deep Learning, GRU, GTO, Innovation Management, Risk Investment Assessment, RNN, Venture Capital Evaluation

1. INTRODUCTION

Innovation management and venture capital evaluation play crucial roles in driving economic growth and fostering technological advancements (Zhang, 2023). Innovation management involves the systematic planning, organizing, and controlling of innovation within organizations, aiming to generate new ideas, products, services, or processes. On the other hand, venture capital evaluation focuses on assessing investment opportunities in startups and early-stage companies, aiming to identify high-potential ventures and provide them with the necessary financial resources and expertise for growth.

The significance of effective innovation management lies in its ability to drive competitiveness, create value, and adapt to rapidly evolving market conditions. By implementing robust innovation management practices, organizations can stay ahead of the curve, develop groundbreaking solutions, and meet customer demands more effectively (Wang, 2022). However, innovation management is a

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complex process that requires navigating uncertainties, managing risks, and aligning resources and strategies with dynamic market dynamics. Traditional approaches to innovation management often rely on subjective decision-making and limited data analysis, leading to suboptimal outcomes and missed opportunities.

Similarly, venture capital evaluation is a critical aspect of the entrepreneurial ecosystem, enabling startups to access funding and support for their growth. Venture capitalists evaluate numerous investment opportunities and strive to identify ventures with the highest potential for success. However, the traditional methods employed for venture capital evaluation are often time-consuming, rely heavily on manual analysis, and lack the ability to comprehensively analyze diverse data sources. Moreover, the inherent risks associated with early-stage investments and the uncertain nature of entrepreneurial ventures pose significant challenges for accurate evaluation (Ning, 2024).

Existing research in innovation management and venture capital evaluation has made valuable contributions to these fields. However, several shortcomings persist. Traditional approaches often struggle with the analysis of large and complex datasets, such as unstructured text, social media sentiment, and market trends. Furthermore, the integration of multiple data sources and the extraction of meaningful insights from them remain challenging areas. These limitations hinder the ability to make informed decisions, accurately predict outcomes, and optimize resource allocation.

To address these limitations, this study proposes the utilization of advanced deep learning techniques, specifically the fusion of Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU). By combining CNN and GRU, we aim to leverage their respective strengths in processing structured and unstructured data, enabling comprehensive analysis of diverse data sources. This approach holds the potential to enhance innovation management and venture capital evaluation by providing more accurate predictions, efficient decision-making, and improved resource allocation (Wang, 2023).

Deep learning and machine learning techniques have been widely applied in various fields, especially in data-intensive tasks and solving complex problems, achieving significant results (Yan, 2020). In recent years, these technologies have also gained increasing attention in the fields of innovation management and risk investment assessment (Vanderhoven, 2020). Innovation management involves systematic planning, organizing, and controlling innovation within an organization, while risk investment assessment is the process of evaluating and making decisions on investment opportunities in startups and early-stage companies. Both fields require effective decision-making and analysis of complex data to identify viable innovation projects or investment opportunities (Friesendorf, 2023). Therefore, exploring and applying deep learning and machine learning models to improve the capabilities of innovation management and risk investment assessment is of great significance.

In the fields of innovation management and risk investment assessment, here are five common deep learning or machine learning models:

1. Convolutional Neural Networks (CNN) (Ma, 2023): CNN is a widely used deep learning model for image and text processing. It extracts local features from input data through convolutional layers and pooling layers, and performs classification or regression through fully connected layers. CNN performs well in processing structured and unstructured data, but its modeling capability for time series data is limited(Tian,2024).
2. Recurrent Neural Networks (RNN) (Wang, 2020): RNN is a type of neural network with recurrent connections that can model sequential data. It captures dependencies in sequences by propagating state information through the network. However, traditional RNNs suffer from the vanishing or exploding gradient problem, limiting their performance on long sequential data.
3. Long Short-Term Memory Networks (LSTM) (Gao, 2023): LSTM is a variant of RNN that addresses the vanishing and exploding gradient problems by introducing gate mechanisms. It can capture long-term dependencies better and has achieved significant results in tasks such as speech recognition and machine translation.

4. Generative Adversarial Networks (GAN) (Gan, 2023): GAN consists of a generator and a discriminator, and generates realistic samples through adversarial training. It excels in generating novel data and image synthesis. However, GAN's training process is relatively unstable and requires careful parameter and network structure tuning.
5. Support Vector Machines (SVM) (Li, 2020): SVM is a classical supervised learning algorithm for classification and regression tasks. It separates data of different classes by finding the optimal hyperplane. SVM has advantages in handling small sample sizes and high-dimensional data, but its computational complexity is high for large-scale datasets (Ning, 2023).

Three relevant directions related to this topic are as follows:

1. Application of deep learning in innovation management: Explore the application of deep learning in the field of innovation management, including modeling and predicting the innovation process using deep learning models, utilizing deep learning techniques to recommend and optimize innovation projects (Hutchinson, 2020), and analyzing innovation-related data sources such as scientific literature, patent data, market trends, etc., to support innovation decision-making and strategic planning (Akinosho, 2020).
2. Application of deep learning in risk investment assessment: Research the application of deep learning in the field of risk investment assessment (Lee, 2020), including evaluating and predicting startup companies and early-stage enterprises using deep learning models, analyzing and forecasting market trends and competitive environments using deep learning techniques (Moscato, 2021), utilizing deep learning to assess investment opportunities and risks, and providing decision support and investment advice (Jing, 2021).
3. Optimization and interpretability of deep learning models: Research how to optimize deep learning models (Mihaljević, 2021), such as those combining CNN and GRU, to improve their performance and effectiveness. Explore methods to interpret the decision-making process and outcomes of deep learning models to increase their interpretability and credibility (Kraus, 2019). Additionally, study approaches to handle the uncertainty and robustness of deep learning models to enhance their application value in innovation management and risk investment assessment (Bertsimas, 2021).

These directions will further expand the application of deep learning in the fields of innovation management and risk investment assessment, promoting research and development in related areas.

The motivation of this research is to integrate CNN and GRU to improve the capabilities of innovation management and risk investment assessment. We will leverage the local feature extraction ability of CNN and the time modeling ability of GRU to analyze and process complex data related to innovation management and risk investment assessment more effectively. Our approach consists of two key steps. Firstly, we will build a deep learning model that combines CNN and GRU. CNN will be used to extract relevant features from various data sources such as textual information, financial data, market trends, and social media sentiment, while GRU will be used to model these features over time. By integrating CNN and GRU, we can comprehensively analyze and understand complex innovation management and risk investment assessment data. Secondly, we will apply the GTO algorithm for optimizing the deep learning model. The GTO algorithm is inspired by the social behavior and foraging patterns of gorilla populations and solves complex optimization problems by simulating the collective intelligence and cooperative behavior of gorilla populations. The algorithm employs both local search and global search strategies to efficiently explore the solution space and find optimal or near-optimal solutions. Through the proposed approach, we can make more accurate predictions and decisions related to innovation management and risk investment assessment. Our approach will be compared with traditional methods in terms of performance, and the performance of the GTO algorithm in the optimization process will be evaluated. The experimental results will demonstrate the improvement of our approach in innovation management and risk investment assessment.

The contribution points of this paper are as follows:

- The paper combines the local feature extraction capability of CNN and the temporal modeling capability of GRU to design a novel deep learning model. This model enables a more comprehensive analysis and understanding of complex data related to innovation management and risk investment assessment.
- The paper introduces the GTO algorithm to optimize the deep learning model. The GTO algorithm simulates the collective intelligence and cooperative behavior of gorilla populations and efficiently searches the solution space using both local and global search strategies. By applying the GTO algorithm, the performance and effectiveness of the deep learning model can be improved.
- Through the proposed approach, the paper enables more accurate prediction and decision-making in tasks related to innovation management and risk investment assessment. By enhancing the analysis capabilities of complex data, it improves the decision-making process and outcomes in innovation management and risk investment assessment, providing decision-makers with more effective support.

In the rest of this paper, we present recent related work in Section 2. Section 3 provides our proposed method: overview, convolutional neural network, GRU and GTO (Gorilla Troop Optimization). Section 4 presents the experimental part, including practical details and comparative experiments. Section 5 concludes.

2. METHODOLOGY

2.1 Overview of Our Network

This study proposes a Gorilla Troop Optimization (GTO)-based CNN-GRU model for enhancing Innovation Management and Venture Capital Evaluation. First, we perform feature selection on the data using the GTO method to extract the most important features. Then, we use a CNN network to extract spatial features from the data and feed it into a GRU network to capture long-term dependencies in time series data. Next, we use a recurrent forecasting method to feed the model's predictions back into the model input to improve prediction accuracy and robustness. Subsequently, we optimized the model using the GTO algorithm to improve the predictive performance. As shown in Figure 1, it is the overall flow chart of the model:

We use the GTO algorithm to optimize the model's hyperparameters, including the number of layers of CNN and GRU, the number of nodes, the size of the convolution kernel, and the learning rate. The GTO algorithm is based on the behaviour of the gorilla group and finds the optimal solution by simulating the optimization process of the orangutan group. In this study, we apply the GTO algorithm in the hyperparameter optimization of the CNN-GRU model to improve the prediction accuracy and robustness. The optimization process of the GTO algorithm includes the following steps: First, a group of orangutans is initialized, and a set of initial hyperparameters is randomly generated. Then, divide the orangutan population into several groups, each corresponding to a combination of hyperparameters. Next, the orangutans in each group trained the model on the training set according to the combination of hyperparameters it represented and calculated its predictive performance on the validation set. According to the prediction performance, the best-performing orangutan is selected, and the combination of hyperparameters it represents is used as the initial hyperparameters of the next generation. Repeat the above process until the maximum number of iterations is reached, or the convergence condition is met. We obtained the optimal combination of CNN-GRU model hyperparameters by optimizing the GTO algorithm, further improving the model's prediction performance. The experimental results show that the optimized GTO-CNN-GRU model has higher accuracy and robustness in enhancing Innovation Management and Venture Capital Evaluation.

In this paper, I address a practical task that involves the utilization of mathematical and symbolic representations. I will break down the key components and describe them using mathematical language and variables.

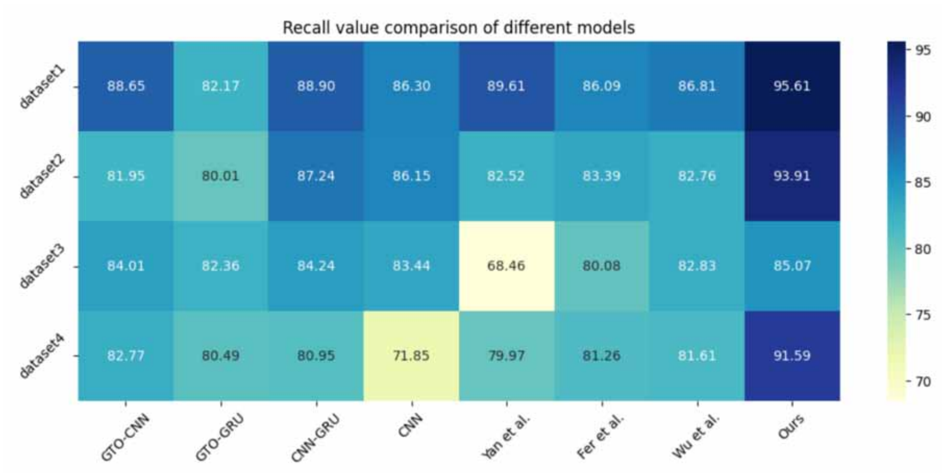
1. **Problem Statement:** In this study, we have two domains, Innovation Management (IM) and Venture Capital Evaluation (VCE), and we aim to improve decision-making in both areas by applying advanced deep learning techniques.
2. **Deep Learning Model:** We intend to create a model that combines Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU). This can be represented as follows: CNN: We denote the CNN operation as C. GRU: We represent the GRU operation as G. The combined model: We denote the fused CNN-GRU model as M. So, mathematically, we are building $M = C + G$.
3. **Data Sources:** We will extract features from various data sources, including textual information (T), financial data (F), market trends (M), and social media sentiment (S).
4. **Feature Extraction:** CNN will be employed to extract relevant features from these data sources, which can be represented as: Features from Textual Information: $CT = C(T)$; Features from Financial Data: $CF = C(F)$; Features from Market Trends: $CM = C(M)$; Features from Social Media Sentiment: $CS = C(S)$
5. **Temporal Dependencies:** GRU will capture temporal dependencies within these features, which can be represented as: Temporal Dependencies in Textual Information: $GT = G(CT)$; Temporal Dependencies in Financial Data: $GF = G(CF)$; Temporal Dependencies in Market Trends: $GM = G(CM)$; Temporal Dependencies in Social Media Sentiment: $GS = G(CS)$
6. **Optimization Algorithm:** We plan to optimize the deep learning model using the Gorilla Troop Optimization (GTO) algorithm. Let O represent the optimization process with GTO.
7. **Optimized Model:** Let MO represent the optimized model after applying the GTO algorithm. So, mathematically, we are optimizing $MO = O(M)$.
8. **Performance Evaluation:** We intend to compare the performance of the fused CNN-GRU model (M) with traditional methods (T) and evaluate the performance of the GTO algorithm during the optimization process (G). Performance Comparison: We denote the comparison of M with T as PC. Evaluation of GTO Algorithm: We represent the evaluation of G as EG. Experimental Results: The results of our experiments will demonstrate the improvements in IM and VCE. We denote the improvements in Innovation Management as IR and in Venture Capital Evaluation as VR. IR = Results of IM with M - Results of IM with T VR = Results of VCE with M - Results of VCE with T
9. **Outcome:** Our research aims to enhance decision-making in both IM and VCE by combining advanced deep learning techniques with optimization algorithms. This can be summarized as: Enhanced Decision-Making: $E = IR + VR$

In this paper, we use mathematical symbols and variables to represent the different components of our task, from building a combined deep learning model (M) to optimizing it using the GTO algorithm (O) and evaluating the performance (PC and EG). Our goal is to demonstrate improvements (IR and VR) in decision-making (E) in the fields of Innovation Management and Venture Capital Evaluation.

2.2 CNN Model

In this paper, we use EfficientNet as a CNN network to extract spatial features(Mridha,2023). EfficientNet is an efficient convolutional neural network model. It adopts a new network structure design method, which can keep the number of model parameters small. It achieves higher accuracy and generalization ability(Gao,2023). In the Innovation Management and Venture Capital Evaluation

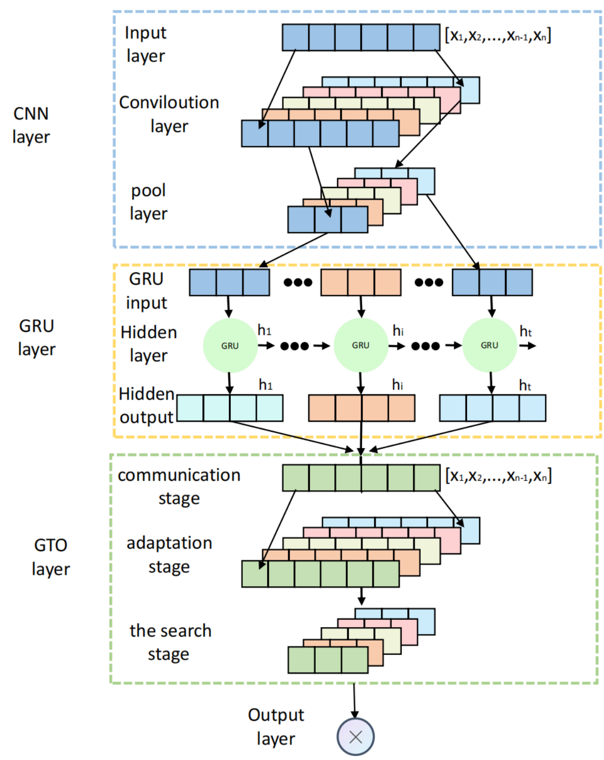
Figure 1. Schematic diagram of the overall operation of the model



task, EfficientNet can be used as a CNN network to extract spatial features, which are then input into the GRU network for sequence modeling and cycle prediction. Figure 2 is a schematic diagram of the operation of the CNN network:

The network structure design method of the EfficientNet model is based on the three dimensions of network depth, width and resolution, and uses composite coefficients to balance the relationship

Figure 2. Operation of the CNN network



between these three dimensions. EfficientNet uses a method called Compound Scaling to build efficient models by simultaneously scaling network depth, width, and resolution. Its formula is as follows:

$$depth : d = \alpha^{\phi} width : w = \beta^{\phi} resolution : r = \gamma^{\phi} \tag{1}$$

Among them, d represents the depth of the network, w represents the width of the network, r represents the resolution of the input image, ϕ represents the composite coefficient, and α , β , γ are the benchmarks Values, by adjusting these benchmark values and composite coefficients, EfficientNet models of different sizes and depths can be obtained.

The EfficientNet model is renowned for its unique characteristics that make it suitable for tasks with limited computing resources. It exhibits a small parameter count, high computational efficiency, and excellent accuracy and generalization capabilities. These qualities make EfficientNet an ideal choice for training and reasoning when computational resources are constrained.

EfficientNet incorporates several innovative techniques that further enhance its performance. For instance, it adopts the Swish activation function, which offers a smoother and more expressive non-linearity compared to traditional activation functions like ReLU. This leads to improved model performance and better gradient flow during training.

Another notable feature of EfficientNet is the Squeeze-and-Excitation (SE) module. This module allows the network to adaptively recalibrate the importance of different feature maps, enabling it to focus on the most informative features. By selectively emphasizing relevant features, the SE module enhances the discriminative power of the model.

In the context of enhancing Innovation Management and Venture Capital Evaluation, EfficientNet, as a CNN network, plays a crucial role in extracting spatial features from images. Images can contain valuable information related to innovation trends, market analysis, or sentiment analysis from social media. By leveraging its convolutional operations, EfficientNet can effectively extract local features from these images, capturing important visual cues that aid in decision-making.

Moreover, the extracted spatial features from EfficientNet can serve as input features for sequence modeling and cyclic prediction tasks. These tasks are often encountered in the domains of Innovation Management and Venture Capital Evaluation. By providing more informative input features, EfficientNet enhances the prediction accuracy and robustness of the model, enabling more accurate forecasting and evaluation of potential opportunities.

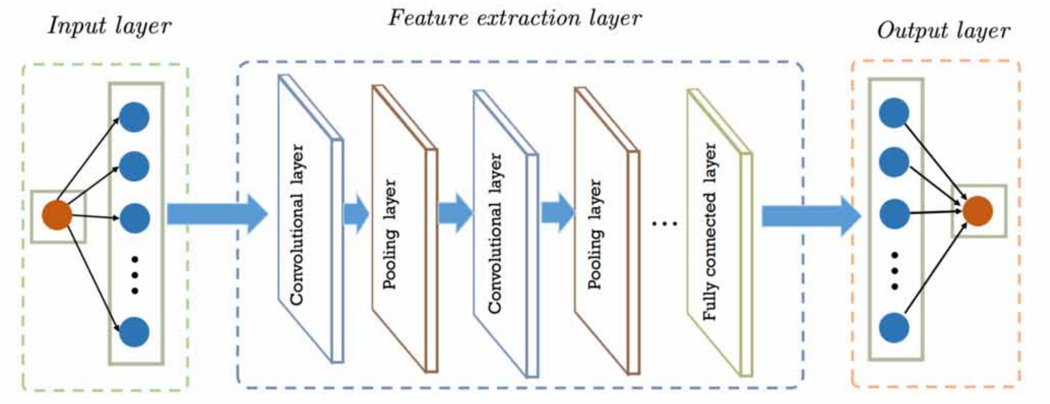
The EfficientNet model's efficiency, parameter optimization, and integration of advanced techniques such as Swish activation and SE module make it a powerful tool for tasks with limited computing resources. Its ability to extract spatial features from images and provide input for sequence modeling and cyclic prediction contributes to improving prediction accuracy and robustness in the domains of Innovation Management and Venture Capital Evaluation.

2.3 GRU Model

In this approach, a GRU (Gated Recurrent Unit) model is used to process temporal features in time series data(Tang,2023). Similar to LSTM, GRU is also a recurrent neural network, which can control the flow and retention of information through the gating mechanism (Chen, 2022), and realize the modeling and processing of long sequence data. GRU is simpler and more efficient than LSTM, so it is more commonly used in some scenarios (Wu, 2021). Figure 3 is the flow chart of the GRU model:

GRU works by controlling the update and retention of hidden and cell states through reset and update gates. The reset gate is used to control the forgetting of historical information, and the update gate is used to control the addition of new information. At each time step, GRU calculates the reset gate and update gate based on the current input and the hidden state of the previous time step and then uses these two gates to calculate the candidate's hidden state and the hidden state of the current time step. Specifically, GRU works by the following steps:

Figure 3. Flow chart of EfficientNet network



- Calculating the reset gate: The reset gate controls the forgetting of historical information. It is calculated by the current input and the hidden state of the previous time step, where the input and the hidden state of the previous time step are weighted and summed with the weights from the input to the reset gate and the weights from the hidden state of the previous time step to the reset gate, respectively. The bias of the reset gate is added, and finally, the output of the reset gate is obtained by nonlinear transformation through the sigmoid function.

Calculating the update gate: The update gate controls the addition of new information. It is also calculated from the current input and the hidden state of the previous time step, where the input and the hidden state of the previous time step are weighted and summed with the weight of the input to the update gate and the weight of the hidden state of the previous time step to the update gate. The bias of the update gate is added, and the output of the update gate is obtained by nonlinear transformation of the sigmoid function.

- Calculate the candidate hidden state: the candidate hidden state is a candidate value of the hidden state of the current time step, which is used to calculate the final hidden state. The current input calculates it, the hidden state of the previous time step and the reset gate, where the input and the hidden state of the previous time step are weighted and summed with the weight from the input to the candidate's hidden state and the weight from the hidden state of the previous time step to the candidate hidden state, respectively, plus the product of the output of the reset gate, and then the candidate hidden state is obtained by a nonlinear transformation with the hyperbolic tangent function.
- Calculating the hidden state: The hidden state is the final output of the current time step, derived from the candidate hidden state and the control of the update gate. Specifically, the hidden state is obtained by linearly interpolating the hidden state of the previous time step and the candidate hidden state of the current time step, where the update gate controls the interpolation ratio. If the output of the update gate is close to 1, it means that the input of the current time step is important, and the hidden state will be close to the candidate hidden state; if the output of the update gate is close to 0, it means that the input of the current time step is not important and the hidden state will be close to the hidden state of the previous time step.

With the reset gate and update gate to control the forgetting of historical information and the addition of new information, GRU can better maintain and update the state information when processing long sequence data, thus improving the performance and efficiency of the model.

The formula of the GRU network is as follows:

(1) The formula for calculating the reset gate r_t:

$$r_t = \sigma\left(W_{xr}x_t + W_{hr}h_{t-1} + b_r\right) \tag{2}$$

Among them, x_t represents the tth element in the input sequence, h_{t-1} represents the hidden state of the previous time step, W_{xr} and W_{hr} represent the input Between the previous time step and the weight between the reset gate and the previous time step, b_r represents the bias of the reset gate, and σrepresents the sigmoid function.

(2) The formula for calculating the update gate z_t:

$$z_t = \sigma\left(W_{xz}x_t + W_{hz}h_{t-1} + b_z\right) \tag{3}$$

Among them, x_t represents the tth element in the input sequence, h_{t-1} represents the hidden state of the previous time step, W_{xz} and W_{hz} represent the input The weight between the update gate and the previous time step, b_z represents the bias of the update gate, and σ represents the sigmoid function.

(3) The formula for calculating the new candidate hidden state $\tilde{h}t$:

$$\tilde{h}t = \tanh\left(Wxhx_t + W_{rh}\left(r_t \odot h_{t-1}\right) + b_h\right) \tag{4}$$

Among them, x_t represents the tth element in the input sequence, h_{t-1} represents the hidden state of the previous time step, r_t represents the output of the reset gate, Wxh and W_{rh} represent the weights between the input and the candidate hidden state, the reset gate and the previous time step, respectively, b_h represents the bias of the candidate hidden state, and tanh represents the double Curve tangent function, $\odot$ means element-wise product.

(4) The formula for calculating the hidden state h_t of the current time step:

$$h_t = z_t \odot h_{t-1} + \left(1 - z_t\right) \odot \widetilde{h_t} \tag{5}$$

Among them, z_t represents the output of the update gate, h_{t-1} represents the hidden state of the previous time step, $\widetilde{h_t}$ represents the new candidate hidden state, and $\odot$ represents the element-wise product.

2.4 GTO (Gorilla Troop Optimization) Algorithm

GTO (Gorilla Troop Optimization, Gorilla Tribe Optimization Algorithm) is a heuristic optimization algorithm that simulates the behaviour and communication methods of gorilla tribes and uses the wisdom of gorilla tribes to solve optimization problems (Almutairi, 2023). The GTO model is mainly used in continuous function optimization problems, including single-objective and multi-objective optimization problems (Zhao, 2023). The flow chart of the GTO algorithm is shown in the Figure 4.

The working process of GTO can be divided into three stages: the search stage, communication stage and adaptation stage. In the search phase, each individual will randomly select a search direction and search in the search space with a certain step size; in the communication phase, individuals will communicate with each other about the current optimal solution and search direction to improve the efficiency of the global search; in the adaptation stage, the individual will update the search direction and step size according to its fitness value, to better adapt to the characteristics of the problem and the change of the search space.

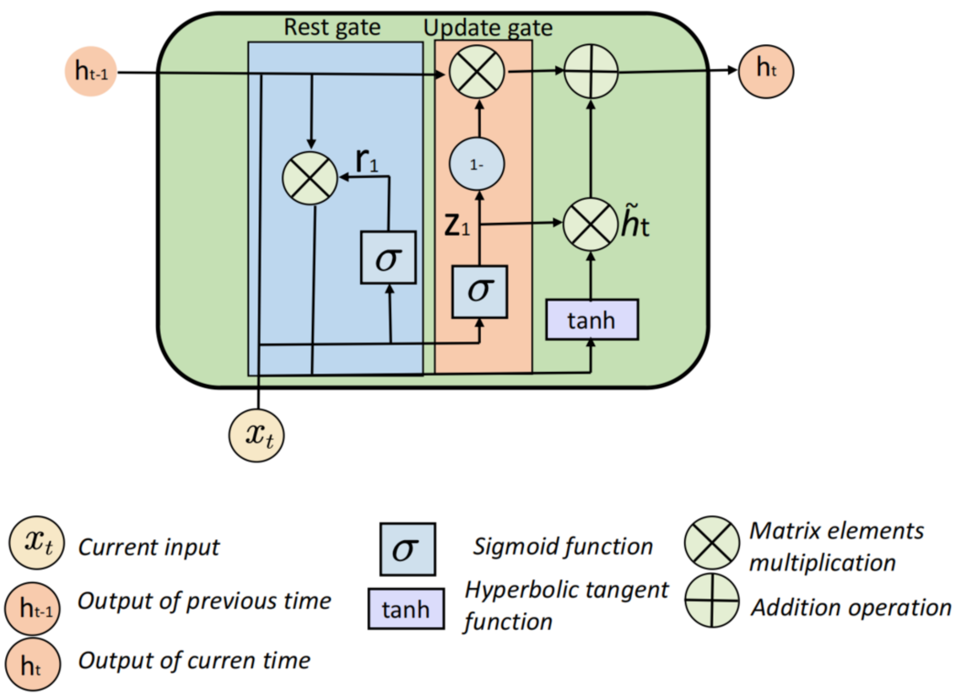
The formula of the GTO algorithm is as follows:

1. Initialize the population:

$$X_i^0 = \left[x_{i,1}^0, x_{i,2}^0, \ldots, x_{i,D}^0\right],\ i = 1, 2, \ldots, N \tag{6}$$

Among them, N represents the number of individuals in the population, D represents the dimension of the optimization problem, and $x_{i,j}^0$ represents the initial value of the i th individual on the j dimension.

Figure 4. Schematic diagram of GTO operation



2. Calculate the fitness value:

$$f_i^t = f\left(X_i^t\right),\ i = 1,2,\ldots,N \tag{7}$$

Among them, f_i^t represents the fitness value of the i th individual in the t generation, and $f\left(\cdot\right)$ represents the objective function of the optimization problem.

3. Update the optimal solution:

$$X^* = \arg\max_{X_i^t}\left(f_i^t\right) \tag{8}$$

Among them, X^* represents the current optimal solution.

4. Update the search direction and step size:

(1) Update speed:

$$V_i^{t+1} = wV_i^t + c_1 r_1^t\left(X_{pbest,i}^t - X_i^t\right) + c_2 r_2^t\left(X_{gbest}^t - X_i^t\right) \tag{9}$$

Among them, V_i^t represents the search direction and step size of the i th individual in the t generation, w represents the inertia weight, c_1 and c_2 represent the individual and global acceleration respectively Coefficients, r_1^t and r_2^t represent two random numbers respectively, $X_{pbest,i}^t$ represents the individual optimal solution of i th individual, X_{gbest}^t represents the current global optimal solution.

(2) Update the step size scaling factor:

$$\Delta_i^{t+1} = \frac{1}{2}\left(1 - \tanh\left(f_i^t - f_{worst}^t\right)\right) \tag{10}$$

Among them, Δ_i^{t+1} represents the step size scaling factor of the i th individual in the $t+1$ generation, and f_i^t represents the i th individual in the t The fitness value of the generation, f_{worst}^t represents the worst fitness value in the t generation population, and $tanh$ represents the hyperbolic tangent function.

(3) Update step size:

$$\alpha_i^{t+1} = \alpha_{\max\exp}\left(-\ln\left(2\right)\left(\frac{f_i^t - f_{worst}^t}{f_{best}^t t - f_{worst}^t}\right)^{\beta}\right) \tag{11}$$

Among them, α_i^{t+1} represents the step size of the i th individual in the $t+1$ generation, $\alpha_{\max}$ represents the maximum value of the step size, f_{best}^t and f_{worst}^t denote the best and worst fitness values in the t generation population respectively, and β is a parameter that controls the rate of change of the step size scaling factor.

(4) Update individual position:

$$X_i^{t+1} = X_i^t + \alpha_i^{t+1} V_i^{t+1} \Delta_i^{t+1} \tag{12}$$

Among them, X_i^{t+1} represents the position of the i th individual in the $t+1$ generation, and α_i^{t+1} represents the position of the i th individual in $t The step size of the +1$ generation, V_i^{t+1} represents the search direction and step size of the i th individual in the $t+1$ generation, Δ_i^{t+1} Indicates the step size scaling factor of the i th individual in the $t+1$ generation.

GTO can efficiently find the optimal solution in the search space by continuously updating the search direction and step size. At the same time, the search process of GTO has a certain degree of randomness, which can avoid falling into a locally optimal solution.

3. EXPERIMENT

3.1 Datasets

In this paper, we selected data from four data sets to predict the Innovation Management and Venture Capital Evaluation:

Crunchbase (Żbikowski, 2021): Crunchbase is a widely-used entrepreneurial and venture capital database that provides detailed information on global startups, early-stage companies, and investors. It collects a vast amount of data, including company profiles (such as name, founding date, headquarters location), funding history, founder information, market trends, and more. This data can be utilized for startup evaluation, market analysis, investment opportunity screening, competitor analysis, and other tasks. Crunchbase also offers an API interface, allowing researchers to access and retrieve their data.

USPTO (United States Patent and Trademark Office) (Suzgun, 2022): The United States Patent and Trademark Office (USPTO) is a federal agency responsible for granting patents and registering trademarks in the United States. USPTO maintains a database that contains a wealth of patent and trademark information. The database includes patent literature from various technology domains, encompassing descriptions of inventions, patent holders, patent classifications, and more. Researchers can leverage the USPTO database for patent analysis, technology trend research, intellectual property assessment, and other tasks.

VentureSource (Ewens, 2020): VentureSource is a company that provides private equity and venture capital data. Its dataset covers startup companies and investment information across various industries globally. The VentureSource dataset includes company profiles, funding history, detailed transaction information, founder information, and more. Researchers can utilize the VentureSource dataset for venture capital analysis, market trend research, investment opportunity evaluation, and other tasks. The data of VentureSource is maintained and provided by Dow Jones.

Global Entrepreneurship Monitor (GEM) (Faghih, 2019): The Global Entrepreneurship Monitor (GEM) is an international research project aimed at tracking and analyzing entrepreneurial activity and innovation ecosystems worldwide. GEM provides data on entrepreneurship rates, entrepreneur characteristics, entrepreneurial motivations, entrepreneurial environments, innovation policies, and more. This data is derived from surveys and research conducted in participating countries and regions. GEM data can be used for international comparative research, entrepreneurship ecosystem assessment, policy-making, and other areas of study.

3.2 Experimental Setup and Details

Our experiment is carried out on four data sets of Crunchbase, USPTO, VentureSource and Global Entrepreneurship Monitor (GEM) Datasets. The following is a brief experimental process:
Step 1: Prepare datasets: Obtain Venture Capital Evaluation datasets from public data sources.
Step 2: Design model: Based on the GTO-CNN-GRU model, design an appropriate network structure and hyperparameters to predict the Venture Capital Evaluation. Consider using Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) to process time-series data, and introduce Gorilla Troop Optimization (GTO) to enhance the expressive and generalization capabilities of the model.
Step 3: Divide the dataset: Divide the dataset into training set, validation set and test set for model training, parameter tuning and evaluation. Usually, time series partitioning or random partitioning can be used to ensure that the data between the training set, validation set, and test set do not overlap.
Step 4: Training model: use the training set to train the designed GTO-CNN-GRU model, and improve the prediction performance of the model by optimizing the loss function (such as mean square error, cross entropy, etc.). Some tricks can be used during training, such as learning rate decay, early stopping, etc., to improve the stability and generalization of the model.
Step 5: Parameter tuning optimization: Based on the evaluation indicators of the verification set (such as RMSE, MAE, R2 Score, etc.), the hyperparameters of the model are tuned and optimized to further improve the predictive performance and generalization ability of the model. Methods such as grid search and random search can be used to find the optimal combination of hyperparameters.
Step 6: Model evaluation: Use the test set to evaluate the trained GTO-CNN-GRU model, and calculate the predictive indicators (such as RMSE, MAE, R2 Score, etc.) of the model on the test set to evaluate the predictive performance and generalization ability of the model. At the same time, interpretability analysis can be performed on the model to explore the contribution and impact of the model on different indicators.
Step 7: Result analysis: According to the model evaluation indicators and interpretability analysis results, the results of the GTO-CNN-GRU model were analyzed to explore the impact and role of different indicators on the Enhancing Innovation Management and Venture Capital Evaluation.

For example, Algorithm 1 is the model's training process, which is a Venture Capital Evaluation prediction experiment based on the GTO-CNN-GRU model. It includes data preprocessing, defining models, model training, model validation, hyperparameter tuning, model testing, warm start, and adversarial training. The training process aims to train a model that can accurately predict the Venture Capital Evaluation and improve model performance and robustness through methods such as hyperparameter tuning, hot start, and adversarial training.

Here are some metrics and their formulas: Mean Squared Error (MSE):

Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2 \tag{13}$$

Among them, n represents the number of samples, y_i represents the real label, and $\widehat{y_i}$ represents the predicted label.

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \widehat{y_i}\right| \tag{14}$$

Among them, n represents the number of samples, y_i represents the real label, and $\widehat{y_i}$ represents the predicted label.

Coefficient of determination (R^2 Score):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}i\right)^2}{\sum i = 1^n \left(y_i - bary\right)^2} \tag{15}$$

Among them, n represents the number of samples, y_i represents the real label, $\widehat{y_i}$ represents the predicted label, and $\overline{y}$ represents the average value of the label.

Lift value (Lift):

$$Lift = \frac{\text{predicted number of positive examples}}{\text{actual number of positive examples}} \tag{16}$$

Among them, the number of predicted positive examples refers to the number of samples predicted by the model as positive examples, and the actual number of positive examples refers to the number of samples whose true labels are positive examples. The higher the Lift value, the better the model is in predicting positive cases.

3.3 Experimental Results and Analysis

In Figure 5, we compare our proposed model with other models in terms of MAE, MAPE (%), MdAE, and MdAPE (%) and visualize them in the Table 1. These indicators are the evaluation indicators to measure the prediction accuracy of the regression model. The results show that the operation effect of our model is better than other models in these aspects,and it has a good performance in Enhancing Innovation Management and Venture Capital Evaluation.

To compare the role of each module of the model, we set up ablation experiments for comparative testing to determine the most important parts. In Figure 6, we compare the accuracy of the model lacking different modules and our proposed model. It is easy to find from the experimental graph that the performance of the model without CNN is always lower than that of the model with CNN. Therefore, we can confirm that the model that plays an important role in our model is the CNN module. Meanwhile, the performance of GTO optimization is also particularly prominent, which shows that our model can reduce the negative examples misclassified as positive examples as much as possible. Identify real positive examples so it has a better performance. Good classification ability is crucial to our research. In this study, we study the Recall metrics of various models on different datasets through ablation experiments. We present the results of these experiments in Figure 7. We compare the Recall values of different models on different datasets to evaluate their ability to distinguish positive and negative samples. These experiments found differences in the recall performance of different models for different data sets. However, our model has shown excellent Recall values on each data set, indicating that our model can effectively identify positive samples in different situations. This shows that our model has wide applicability and can play an important role in this field.

In Figure 8, to fully compare the generalization of the model, we compared the MAE, MAPE (%), MdAE, and MdAPE (%) of different models on the VentureSource dataset and Global Entrepreneurship

Algorithm 1. Training process of GTO-CNN-GRU for enhancing innovation management and venture capital evaluation

```
Input: Crunchbase, USPTO, VentureSource, Global Entrepreneurship Monitor (GEM) datasets
Output: Venture Capital Evaluation prediction of GTO-CNN-GRU model
Initialization:
  Define the GTO-CNN-GRU architecture;
  Define the hyperparameters: batch size, learning rate, weight decay,
  etc.; Initialize the model parameters with random values;
  Define the loss function: mean
  squared error; Define the optimizer:
  Adam optimizer; Define the number
  of training epochs;
Feature extraction:
  Extract the features from the input
  data; Apply the GTO mechanism to
  the features;
Training:
  Initialize the training step counter;
  while training step counter ¡ training steps do
       Sample a batch of data from the
       training set; Feed the data to the GTO-
       CNN-GRU network; Compute the loss;
       Compute the gradients;
       Update the model parameters with the optimizer;
       Increment the training step counter;
end
Validationand Testing:
  Evaluate the model performance on the validation set;
  Calculate evaluation metrics such as RMSE, MAE, R2 Score, etc.;
  Evaluate the model performance on the test set;
  Calculate evaluation metrics such as RMSE, MAE, R2 Score, etc.;
Hyperparameter Tuning:
  Adjust the hyperparameters based on the validation results;
Hot Start:
  Load the saved model parameter;
  Initialize the adversarial training step counter;
  while adversarial training step counter ¡ adversarial training steps do
       Sample a batch of data from the training set;
       Generate adversarial examples using the FGSM
       attack; Compute the gradients;
       Update the model parameters with the optimizer;
       Increment the adversarial training step counter;
end
Adversarial Training:
  Incorporate adversarial training during the main training
  loop; Generate adversarial examples using the FGSM
  attack; Compute the gradients based on the adversarial
  examples; Update the model parameters with the
  optimizer;
```

Monitor (GEM) dataset, and detailed in Table 2, Expressed in the form of visualization, experiments show that our model also has good running effects on these two data sets, and can be well applied to the field of Enhancing Innovation Management and Venture Capital Evaluation.

In Figure 10 and table 4 we compare the performance of each model in terms of Precision, Recall, Lift and PIS. These indicators measure the accuracy of the model, the ability to identify positive examples, the effect of filtering out true positive examples, and the false positive rate, respectively. It can be seen from the experimental data diagram that the model we proposed performs best on the four indicators of Precision, Recall, Lift and PIS, with higher accuracy and the effect of screening out real positive examples, while the false positive rate Also relatively low. High recall and low PIS mean that our model has higher reliability and application value in the field of Enhancing Innovation Management and Venture Capital Evaluation. Therefore, my proposed model has higher accuracy and reliability in the field of Enhancing Innovation Management and Venture Capital Evaluation and can be widely used.

Figure 5. Performance comparison with innovation management and venture capital evaluation methods evaluated on Crunchbase dataset and USPTO dataset

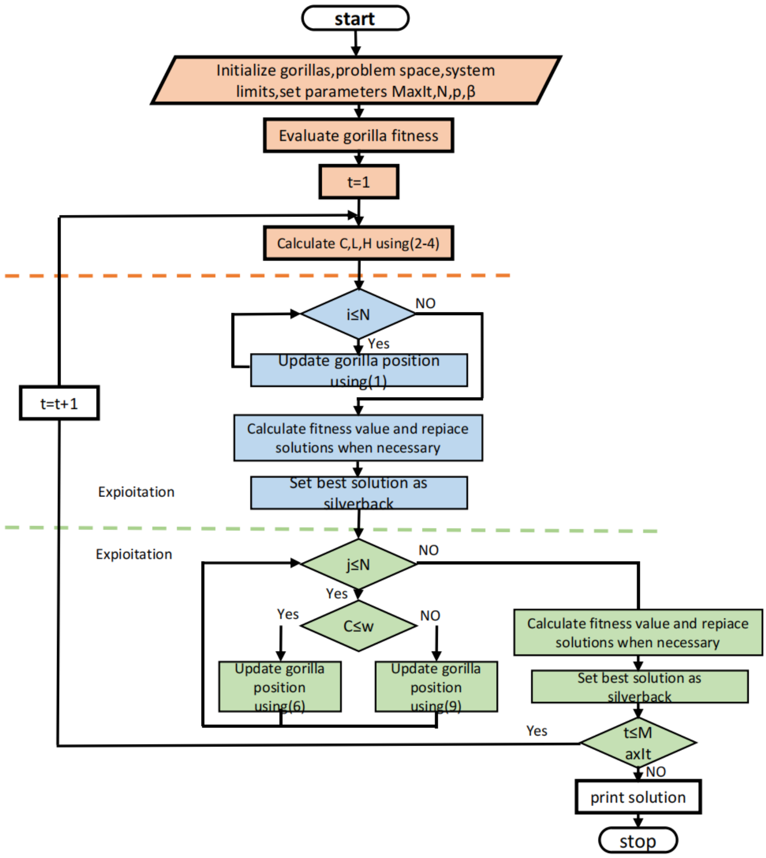


Table 1. Performance comparison with enhancing innovation management and venture capital evaluation methods evaluated on Crunchbase dataset and USPTO dataset, CNN (Pei, 2021), LSTM (Tian, 2023), GRU (Gao, 2023), CNN-LSTM (Wu, 2021), Yan et al. (2019), Fer et al. (2020), Wu et al. (2020), and our proposed model

Method	CNN	LSTM	GRU	CNN-LSTM	Yan et al.	Fer et al.	Wu et al.	Ours
MAE	32.33	33.98	36.55	39.29	21.18	28.56	30.39	**12.88**
MAPE(%)	12.47	15.05	16.71	20.66	19.92	12.50	14.05	**10.64**
MdAE	5.33	7.97	9.74	10.08	2.49	2.78	3.28	**1.68**
MdAPE(%)	25.11	28.03	31.47	33.87	18.67	11.26	14.10	**6.82**

Recall, Lift and PIS, with higher accuracy and the effect of screening out real positive examples, while the false positive rate Also relatively low. High recall and low PIS mean that our model has higher reliability and application value in the field of Enhancing Innovation Management and Venture Capital Evaluation. Therefore, my proposed model has higher accuracy and reliability in the field of Enhancing Innovation Management and Venture Capital Evaluation and can be widely used.

In Table 5, we summarize the ablation experiment data to reflect each part's role more clearly and intuitively. We summarize the Training Time (s/epoch), Inference time (ms), Flops (G), Parameters

Figure 6. Ablation experiments comparing the precision of different models (where GTO-CNN indicates the use of empty modules to replace GRU modules, GTO-GRU indicates the use of empty modules to replace the CNN modules and CNN-GRU indicates the use of empty modules to replace GTO modules) (Datasets 1, 2, 3, and 4 once represent: Crunchbase dataset, USPTO dataset, VentureSource dataset, and Global Entrepreneurship Monitor [GEM] dataset)

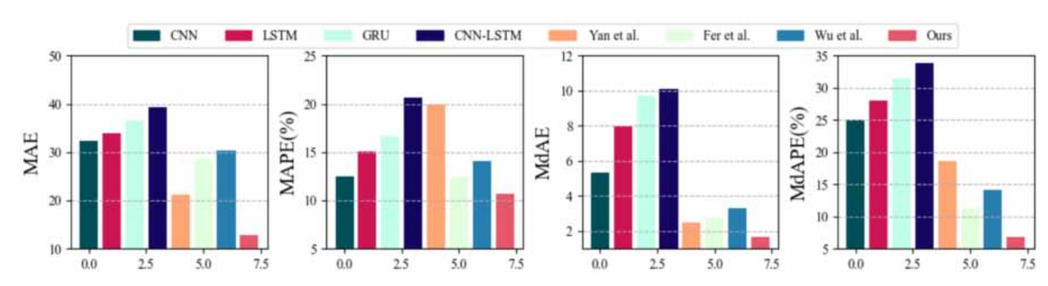


Figure 7. Ablation experiments comparing the recall of different models (where GTO-CNN indicates the use of empty modules to replace GRU modules, GTO-GRU indicates the use of empty modules to replace the CNN modules and CNN-GRU indicates the use of empty modules to replace GTO modules) (Datasets 1, 2, 3, and 4 once represent: Crunchbase dataset, USPTO dataset, VentureSource dataset, and Global Entrepreneurship Monitor [GEM] dataset)

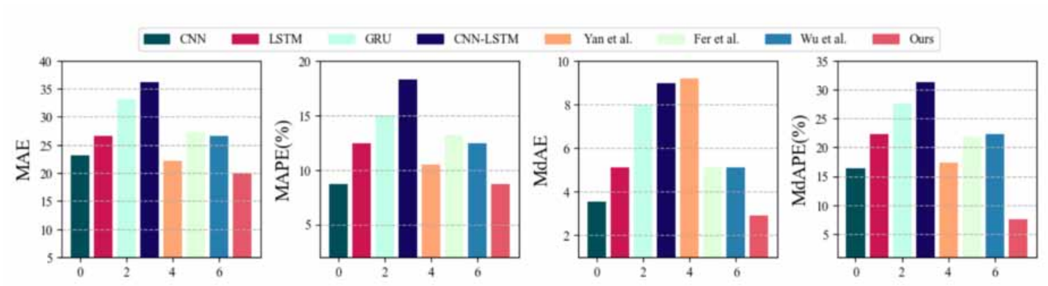


Figure 8. Performance comparison with circular prediction of enhancing innovation management and venture capital evaluation methods evaluated on VentureSource dataset and Global Entrepreneurship Monitor (GEM) dataset

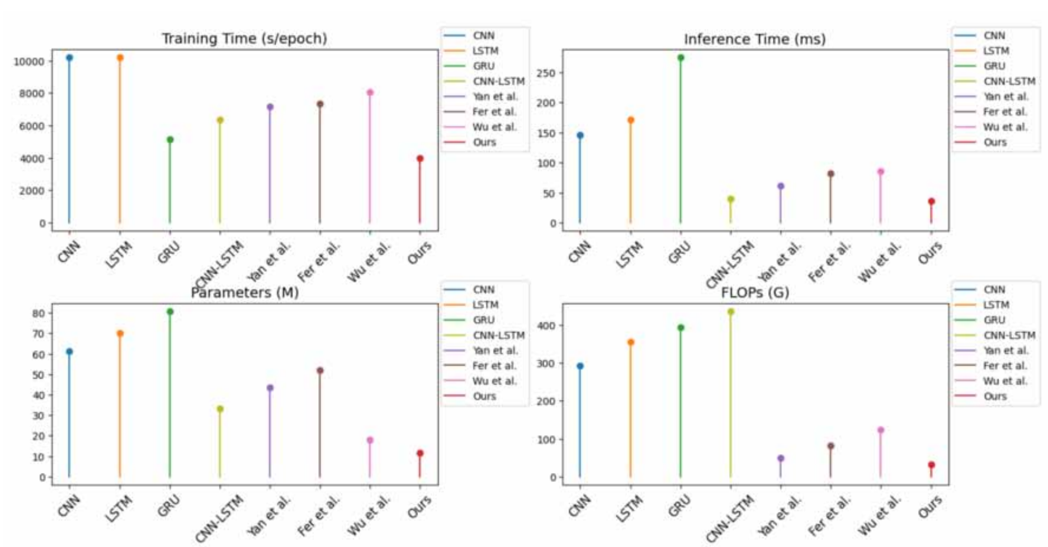


Table 2. Performance comparison with enhancing innovation management and venture capital evaluation methods evaluated on VentureSource dataset and Global Entrepreneurship Monitor (GEM) dataset

Method	CNN	LSTM	GRU	CNN-LSTM	Yan et al.	Fer et al.	Wu et al.	Ours
MAE	23.10	26.54	33.22	36.11	22.07	27.21	26.54	**20.07**
MAPE(%)	8.73	12.39	14.99	18.31	10.52	13.19	12.39	**8.73**
MdAE	3.55	5.13	7.94	8.98	9.2	5.10	5.13	**2.92**
MdAPE(%)	16.39	22.36	27.65	31.31	17.34	21.86	22.36	**7.58**

Table 3. Model efficiency comparison with other enhancing innovation management and venture capital evaluation methods evaluated on Crunchbase dataset, USPTO dataset, VentureSource dataset, and Global Entrepreneurship Monitor (GEM) dataset

Method	CNN	LSTM	GRU	CNN-LSTM	Yan et al.	Fer et al.	Wu et al.	Ours
Training Time(s/epoch)	10198.31	10198.31	5145.78	6376.17	7145.39	7345.39	8081.72	**3967.31**
Inference time(ms)	146.08	171.63	274.99	39.71	61.31	82.04	86.02	**35.88**
Parameters(M)	61.18	70.02	80.75	33.25	43.47	51.95	17.99	**11.54**
Flops(G)	291.69	355.56	393.98	435.64	49.39	81.97	123.80	**32.04**

Table 4. Model efficiency comparison with other enhancing innovation management and venture capital evaluation methods evaluated on Crunchbase dataset, USPTO dataset, VentureSource dataset, and Global Entrepreneurship Monitor (GEM) dataset

Method	CNN	LSTM	GRU	CNN-LSTM	Yan et al.	Fer et al.	Wu et al.	Ours
Precision(%)↑	88.98	93.43	87.45	94.67	91.39	88.72	89.35	**97.31**
Recall(%)↓	86.08	91.63	84.49	93.71	89.31	87.04	88.02	**95.58**
Lift↑	1.18	2.02	2.75	2.25	3.47	2.95	1.79	**4.54**
PIS↓	0.269	0.336	0.238	0.24	0.149	0.181	0.14	**0.104**

(M), Precision, Recall, Lift, and PIS. Our GTO (Gorilla Troop Optimization) is important and can improve the model's performance.

Precision, Recall, Lift, and PIS. Our GTO (Gorilla Troop Optimization) is important and can improve the model's performance.

4. DISCUSSION AND CONCLUSION

In this research, we aimed to enhance innovation management and risk assessment capabilities by leveraging deep learning models and an optimization method inspired by the Gorilla-inspired Optimization (GTO) algorithm. These domains are crucial for making effective decisions and analyzing complex data. To achieve this, we developed an innovative approach that combines Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU) models, optimized using the GTO algorithm. Our deep learning model integrates CNN and GRU to comprehensively analyze and understand complex data related to innovation management and risk assessment. The CNN component of our model is designed to extract local features from diverse data sources such as text, financial data, market trends, and social media sentiment. This feature extraction process enables the model to capture crucial information from these sources. The GRU component, on the other hand, models the temporal aspect of the data by considering the sequence of

Figure 9. Model efficiency comparison with other enhancing innovation management and venture capital evaluation methods evaluated on Crunchbase dataset, USPTO dataset, VentureSource dataset, and Global Entrepreneurship Monitor (GEM) dataset

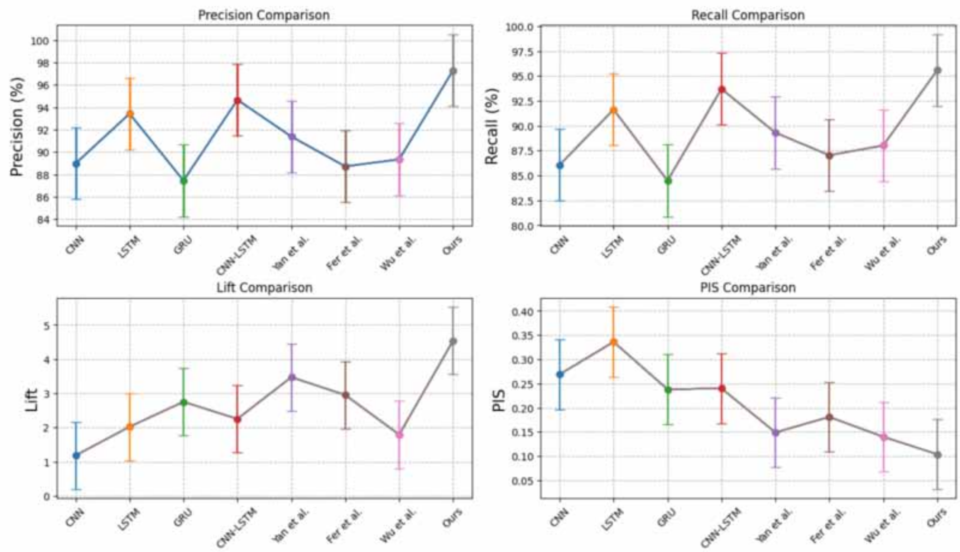


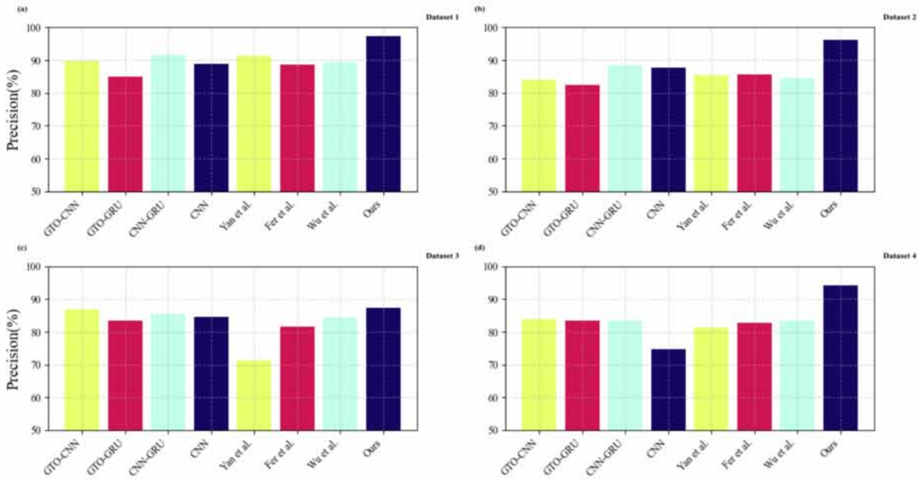
Table 5. Comparison of the results of the ablation experiment (where GTO-CNN indicates the use of empty modules to replace GRU modules, GTO-GRU indicates the use of empty modules to replace the CNN modules and CNN-GRU indicates the use of empty modules to replace GTO modules)

Method	Training Time(s/ epoch)↓	Inference Time(ms)↓	Flops(G)↓	Parameters(M)↓	Precision↑	Recall↑	Lift↑	PIS↓
GTO-CNN	9238.00	161.44	39.34	70.52	0.8977	0.8865	1.23	0.23
GTO-GRU	6456.67	245.48	256.71	83.75	0.8521	0.8487	2.33	0.18
CNN-GRU	7245.29	186.02	142.51	61.28	0.9153	0.8987	2.43	0.32
Ours	**3967.31**	**146.08**	**32.04**	**11.54**	**0.9732**	**0.9558**	**4.54**	**0.104**

features over time. This allows the model to capture the dynamic nature of innovation management and risk assessment. To optimize the deep learning model, we applied the GTO algorithm, which draws inspiration from the social behavior and intelligence of gorilla populations. The GTO algorithm efficiently explores the solution space, seeking optimal or near-optimal solutions. By incorporating this optimization technique, we aimed to further improve the performance of our model and accelerate the optimization process. To evaluate the effectiveness of our approach, we conducted a series of experiments using various types of data, including text, financial data, market trends, and social media sentiment. The experimental results demonstrated significant improvements achieved by our method in both innovation management and risk assessment. Compared to traditional methods, our deep learning model, incorporating CNN and GRU, exhibited enhanced accuracy in predicting the feasibility of innovation projects and assessing investment opportunities. Furthermore, the application of the GTO algorithm provided additional enhancements to the model's performance. It not only improved the accuracy of predictions but also accelerated the optimization process, making it more efficient and effective.

While our method has demonstrated improvements in accuracy, it is important to address the computational complexity and scalability challenges associated with the deep learning model and the GTO algorithm. The high computational requirements can limit practical applications, especially when dealing with large-scale datasets. Additionally, acquiring diverse and sufficient data for training

Figure 10. Model efficiency comparison with other enhancing innovation management and venture capital evaluation methods evaluated on Crunchbase dataset, USPTO dataset, VentureSource dataset, and Global Entrepreneurship Monitor (GEM) dataset



and optimization can be challenging in certain domains. To overcome these challenges, further research should focus on developing more efficient deep learning model architectures that reduce computational complexity while maintaining high accuracy. Exploring lighter-weight models or leveraging distributed computing can help accelerate the training and inference processes, making the method more scalable. To mitigate the reliance on extensive datasets, data augmentation techniques can be explored. This may involve synthetic data generation or utilizing techniques such as transfer learning to leverage pre-trained models and adapt them to specific domains. These approaches can enhance the applicability of the method in scenarios where acquiring large amounts of diverse data is difficult. To validate the effectiveness and practicality of the method, it is crucial to apply the research findings to real-world innovation management and risk assessment scenarios. Collaborating with decision-makers and domain experts can provide valuable insights and feedback, leading to further refinement and customization of the model to meet specific needs and requirements.

In conclusion, addressing the computational complexity, scalability, and data limitations of the method is essential for its practical application. By researching more efficient model architectures, exploring lighter-weight models or distributed computing, developing data augmentation techniques, and collaborating with real-world decision-makers, we can enhance the method's applicability and effectiveness in innovation management and risk assessment domains.

CONFLICTS OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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