

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

Chen Quan, KEYI College of Zhejiang Sci-Tech University, China*

Baoli Lu, University of Portsmouth, UK

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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*Corresponding Author

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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.

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