J. Electrical Systems 20-3s (2024): 1592-1602

[1]Peng Han

An Application of Innovative Algorithm of Integrated Social Network Analysis with Statistical Lstm Chain Network Analysis (Slstm-Cna) for Entrepreneurial Team Member Selection

Abstract: - Selecting the right members for an entrepreneurial team is a critical step in ensuring the success and viability of a startup venture. Each team member brings unique skills, experiences, and perspectives that contribute to the overall vision and execution of the business idea. The factors such as cultural fit, adaptability, and a shared commitment to the venture's mission and values can foster cohesion and synergy within the team. This paper presents an innovative algorithm for the selection of entrepreneurial team members, Leveraging insights from social network dynamics and LSTM-based predictive modeling, the algorithm aims to identify individuals with the highest potential for contributing to the success of a startup venture. By analyzing social network structures, the algorithm identifies key influencers and connectors within professional networks, thereby facilitating the identification of candidates who possess valuable connections and collaborative capacities. Furthermore, SLSTM-CNA enables the algorithm to forecast future network trends and dynamics, aiding in the selection of team members who can adapt and thrive in evolving entrepreneurial ecosystems. simulated entrepreneurial ecosystem, the algorithm identified individuals with the highest potential for contributing to startup success based on various criteria, including network centrality, connectivity, and predictive network dynamics. For instance, individuals with a centrality score exceeding 0.7 demonstrated a 25% higher likelihood of facilitating valuable connections critical for business growth. Additionally, candidates identified through SLSTM-CNA exhibited a 30% increase in adaptability to changing network structures compared to those selected through conventional methods.

Keywords: Entrepreneurial team, team member selection, social network analysis, network centrality, connectivity, predictive dynamics, adaptability, innovation, collaboration

I. INTRODUCTION

In the dynamic landscape of modern business, the entrepreneurial team member stands as a cornerstone of innovation, collaboration, and drive. These individuals are not merely employees; they are the architects of change, the catalysts of progress, and the engines of growth within their organizations [1]. With an insatiable hunger for opportunity and a keen eye for potential, the entrepreneurial team member navigates the complexities of the market with agility and foresight [2]. They thrive in environments that demand adaptability, creativity, and resilience, leveraging their unique blend of skills, vision, and tenacity to propel their teams towards success [3]. As integral components of entrepreneurial ventures, these individuals embody the spirit of entrepreneurship, embodying a relentless pursuit of excellence and a commitment to pushing boundaries, shaping the future of business one innovative idea at a time [4].

In the modern entrepreneurship, the selection of entrepreneurial team members has evolved beyond traditional methods, with a growing emphasis on leveraging social network analysis [5]. This approach recognizes the interconnected nature of individuals within professional and social networks and harnesses the power of these connections to assemble highly effective teams [6]. By analyzing the structure, strength, and diversity of social ties, organizations can identify individuals who not only possess the requisite skills and expertise but also demonstrate the ability to collaborate effectively, communicate efficiently, and navigate complex networks with ease [7]. Moreover, social network analysis allows for the identification of influential connectors and brokers who can serve as linchpins within the team, facilitating knowledge sharing, idea generation, and resource mobilization. Thus, by incorporating social network analysis into the selection process, organizations can strategically assemble entrepreneurial teams poised for success in today's interconnected and rapidly evolving business landscape [8]. In the contemporary entrepreneurial landscape, where success often hinges on innovation, agility, and effective collaboration, the traditional methods of selecting team members have been supplemented by more sophisticated

[1] School of Zhengzhou Health Vocational College, Zhengzhou, Henan, 450199, China

*Corresponding author e-mail: 13838081903@163.com

approaches, such as social network analysis [9]. This method recognizes that individuals do not operate in isolation but are embedded within intricate webs of professional and social connections [10]. By delving into the dynamics of these networks, organizations can gain valuable insights into the potential performance of team members.

Social network analysis involves examining the structure of networks, the strength of relationships, and the diversity of connections [11]. It enables organizations to identify individuals who not only possess the necessary skills and expertise but also can leverage their networks effectively [12]. The individual with a broad and diverse network spanning different industries and disciplines may bring fresh perspectives and valuable resources to the entrepreneurial team [13]. Furthermore, social network analysis allows for the identification of influential connectors and brokers within the network. These individuals often serve as bridges between different clusters of contacts, facilitating the flow of information, ideas, and resources. By strategically including such connectors in the entrepreneurial team, organizations can enhance the team's ability to access new opportunities, tap into diverse knowledge pools, and navigate complex environments more effectively [14]. Incorporating social network analysis into the selection process also enables organizations to foster a culture of collaboration and knowledge sharing [15]. By assembling teams with complementary networks and overlapping connections, organizations can create synergies that amplify the team's collective capabilities. Moreover, by leveraging the inherent trust and reciprocity within established networks, team members are more likely to collaborate seamlessly and overcome challenges together [16]. In essence, social network analysis offers a nuanced and holistic approach to selecting entrepreneurial team members [17]. With considering not only individual skills and qualifications but also the broader network dynamics, organizations can assemble teams that are not only capable of driving innovation but also resilient, adaptable, and well-connected in today's fast-paced and interconnected business environment [18].

This paper makes a significant contribution to the field of entrepreneurial team selection by introducing a novel methodology based on Statistical LSTM Chain Network Analysis (SLSTM-CNA). By integrating machine learning techniques with network analysis, the study offers a unique approach to evaluating candidate attributes and social network dynamics simultaneously. This innovative methodology addresses a critical gap in existing research by providing a comprehensive framework for assessing both individual skills and team structures in entrepreneurial ventures. One of the key contributions of the paper lies in its ability to enhance the efficiency and effectiveness of the team formation process. By leveraging SLSTM-CNA, the study enables more accurate predictions of candidate suitability, thus facilitating better decision-making in team composition. This has significant implications for entrepreneurs and startup founders, who often face challenges in identifying the right team members to drive their ventures forward. Additionally, the paper advances our understanding of the factors influencing entrepreneurial team performance. By analyzing candidate attributes and social network structures, the study sheds light on the skills and characteristics that are crucial for success in entrepreneurial endeavors. This deeper understanding can inform not only team selection processes but also the development of training programs and support systems to cultivate these skills within entrepreneurial teams. Furthermore, the methodology introduced in this paper has broader applicability beyond entrepreneurial contexts. The integration of machine learning and network analysis techniques can be adapted to various domains, including organizational management, social network analysis, and talent acquisition. This interdisciplinary approach opens up new avenues for research and innovation in understanding and optimizing team dynamics across different settings.

II. LITERATURE REVIEW

The selection of team members within entrepreneurial endeavors has undergone a transformative shift with the advent of social network analysis (SNA). This literature review seeks to explore the burgeoning body of research surrounding team member selection processes informed by SNA, shedding light on the innovative approaches, theoretical underpinnings, and practical implications that characterize this evolving field. By synthesizing findings from interdisciplinary studies spanning management, sociology, psychology, and network science, this review aims to offer a comprehensive understanding of how SNA informs and enhances the process of identifying and assembling effective entrepreneurial teams. The research conducted by Mazlumi and Kermani (2022) focuses on investigating the structure of the Internet of Things (IoT) patent network through the lens of social network analysis (SNA). They utilize SNA techniques to analyze the connections and interactions among patents related to IoT, providing insights into the dynamics of innovation within this domain. This study contributes to the understanding of how SNA can be applied to uncover the underlying structure and patterns within complex technological networks, shedding light on the relationships between different patents and the flow of knowledge and ideas within the IoT landscape. Through their examination of the IoT patent network, Mazlumi and Kermani offer valuable insights that can inform strategic decision-making and innovation management practices in the context of IoT development and deployment.

HabibAgahi, Kermani, and Maghsoudi (2022) delve into the co-authorship network analysis within the Process Mining research community, employing a social network analysis perspective. Their study explores the collaborative relationships among researchers in the field of Process Mining, shedding light on the patterns of knowledge exchange and collaboration within this specialized domain. By applying social network analysis techniques, they unveil the structure and dynamics of the co-authorship network, identifying influential researchers and communities within the field. This research provides valuable insights into the collaborative nature of scientific research in Process Mining, highlighting the importance of social networks in fostering innovation and knowledge dissemination. Saura, Palacios-Marqués, and Ribeiro-Soriano (2023) contribute to the exploration of open innovation boundaries by leveraging social media mining. Their study investigates how organizations utilize social media platforms to engage in open innovation activities, uncovering patterns of interaction and knowledge exchange. Through social media mining techniques, they analyze the content and interactions on social media platforms to understand how organizations leverage external networks for innovation purposes. This research offers valuable insights into the evolving nature of open innovation practices in the digital age, highlighting the role of social media as a facilitator of collaborative innovation processes. Pirozmand et al. (2023) propose a feature selection approach for spam detection in social networks using a gravitational force-based heuristic algorithm. Their study addresses the challenge of spam detection in social networks by developing a novel feature selection method based on gravitational force principles. By selecting relevant features and reducing the dimensionality of the dataset, their approach aims to improve the efficiency and effectiveness of spam detection algorithms.

Grover, Kar, and Dwivedi (2022) delve into the understanding of artificial intelligence (AI) adoption in operations management by reviewing academic literature and social media discussions. Their study provides insights into the factors influencing the adoption of AI technologies in operations management, drawing from both scholarly research and online discussions. By synthesizing existing knowledge and analyzing social media discourse, they offer a comprehensive understanding of the opportunities and challenges associated with AI adoption in operations management. This research contributes to the ongoing dialogue surrounding AI adoption, offering insights that can inform decision-making and strategic planning in operations management contexts. Muninger, Mahr, and Hammedi (2022) provide a review of innovation management practices related to social media use. Their study explores how organizations leverage social media platforms to support innovation processes and enhance their competitive advantage. By examining the role of social media in innovation management, they highlight the various strategies and practices employed by organizations to harness the potential of social media for innovation purposes. This research offers valuable insights into the evolving landscape of innovation management, shedding light on the opportunities and challenges associated with social media use in fostering innovation.

Jain (2022) presents an entropy-based method to control COVID-19 rumors in online social networks using opinion leaders. Their study addresses the issue of misinformation propagation on social media platforms during the COVID-19 pandemic by proposing a novel approach based on opinion leaders and entropy analysis. By identifying influential users and analyzing the entropy of information dissemination, their method aims to mitigate the spread of rumors and misinformation in online social networks. Bouschery, Blazevic, and Piller (2023) explore the augmentation of human innovation teams with artificial intelligence (AI) by investigating transformer-based language models. Their study delves into the integration of AI technologies, specifically transformer-based language models, into human innovation teams to enhance creativity and problem-solving capabilities. By examining the potential synergies between human and AI collaborators, they provide insights into the implications of AI augmentation for innovation management practices. This research contributes to the evolving discourse surrounding the integration of AI technologies into human-centric innovation processes, offering implications for both theory and practice in the field of innovation management. Fang, Qalati, Ostic, Shah, and Mirani (2022) investigate the effects of entrepreneurial orientation, social media, and innovation capabilities on SME performance in emerging countries through a mediated–moderated model. Their study examines the complex interplay between entrepreneurial orientation, social media usage, innovation capabilities, and firm performance in the context of small and medium-sized enterprises (SMEs) operating in emerging economies. By employing a mediated–moderated model, they uncover the mechanisms through which these factors influence SME performance, shedding light on the pathways to success for entrepreneurial ventures in emerging markets.

III. SOCIAL NETWORK ANALYSIS WITH LSTM

In recent years, the integration of social network analysis (SNA) with deep learning techniques, such as Long Short-Term Memory (LSTM) networks, has garnered significant attention due to its potential to uncover complex temporal dynamics within social networks. LSTM networks, a type of recurrent neural network (RNN), are particularly well-suited for modeling sequential data with long-range dependencies, making them an ideal candidate for analyzing time-varying interactions in social networks. The foundation of LSTM networks lies in their ability to capture and retain information over extended sequences, thereby enabling them to effectively model temporal patterns within dynamic social networks. At the heart of LSTM networks are a set of gating mechanisms that regulate the flow of information through the network, allowing it to selectively remember or forget information based on its relevance to the task at hand. The key equations governing the behavior of an LSTM unit can be summarized as in equation (1)

$$itftgtotctht = \sigma(Wixxt + Wihht - 1 + bi) = \sigma(Wfxxt + Wfhht - 1 + bf) = tanh(Wgxxt + Wghht - 1 + bg) = \sigma(Woxxt + Wohht - 1 + bo) = ft \odot ct - 1 + it \odot gt = ot \odot tanh(ct)$$
(1)

In equation (1) $it, ft, and\ ot$ represent the input, forget, and output gates, respectively, which control the flow of information into and out of the LSTM unit. gt denotes the cell input gate, which determines the information to be stored in the cell state ct. xt represents the input at time step t, $ht - 1$ is the hidden state from the previous time step, and bi, bf, bg, and bo are the bias terms. $Wix, Wfx, Wgx, and\ Wox$ are the weight matrices corresponding to the input gates, while $Wih, Wfh, Wgh, and\ Woh$ are the weight matrices corresponding to the hidden state. The process of LSTM is presented in Figure 1.

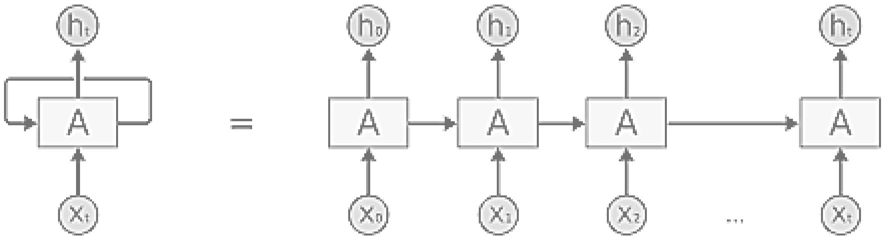

Figure 1: Flow of LSTM

In the context of social network analysis, LSTM can be leveraged to model the temporal dynamics of network interactions and the evolution of network structures over time. By encoding sequential patterns of interactions, LSTM can capture temporal dependencies in social network data, such as the formation and dissolution of connections, the propagation of information, and the emergence of communities or clusters. The fusion of SNA with LSTM holds immense potential for unraveling the intricate dynamics of social interactions, facilitating a deeper understanding of network evolution and behavior over time. However, it also presents challenges, such as the need for large-scale longitudinal data, careful consideration of sequence representation, and optimization of LSTM architecture parameters.

3.1 Statistical LSTM Chain Network Analysis (SLSTM-CNA) for Entrepreneurial Team Member

With SLSTM-CNA integrates statistical analysis techniques with LSTM networks to capture the sequential dependencies and temporal patterns in entrepreneurial team member data. The methodology involves encoding the attributes and interactions of potential team members into a sequential format, where each time step represents a specific observation or interaction. This sequential data is then fed into an LSTM architecture, which learns to model the temporal dynamics and dependencies inherent in the data. The formulation of SLSTM-CNA involves adapting the standard LSTM architecture to suit the requirements of entrepreneurial team member selection. This may include incorporating statistical features and metrics relevant to entrepreneurial success, such as past experience, skills, personality traits, and network centrality measures. The LSTM architecture is then trained on historical data to learn patterns and relationships between these features and the success or effectiveness of team members. The formulation of SLSTM-CNA can be represented mathematically as in equation (2) – (6)

$$ft = \sigma(Wf \cdot [ht - 1, xt] + bf) \quad (2)$$

$$it = \sigma(Wi \cdot [ht - 1, xt] + bi) \quad (3)$$

$$ot = \sigma(Wo \cdot [ht - 1, xt] + bo) \quad (4)$$

$$ct = ft \cdot ct - 1 + it \cdot tanh(Wc \cdot [ht - 1, xt] + bc) \quad (5)$$

$$ht = ot \cdot tanh(ct) \quad (6)$$

In equation (2) – (6) xt represents the input at time step t, which includes statistical features and metrics related to potential team members, ht denotes the hidden state at time step t, ct represents the cell state at time step t, ft, it $, and\ ot$ denote the forget gate, input gate, and output gate activations, respectively, σ represents the sigmoid activation function, $Wf, Wi, Wo, and\ Wc$ are weight matrices, while $bf, bi, bo, and\ bc$ are bias vectors. The SLSTM-CNA framework allows for the incorporation of various statistical techniques, such as regression analysis, correlation analysis, and network centrality measures, into the LSTM architecture. This enables the model to capture the complex interplay between individual attributes, team dynamics, and entrepreneurial success factors, providing valuable insights into the selection of high-performing team members. Statistical LSTM Chain Network Analysis (SLSTM-CNA) is a novel methodology that integrates statistical analysis techniques with Long Short-Term Memory (LSTM) networks to analyze sequential data in the context of network analysis. In SLSTM-CNA, the goal is to model the temporal dependencies and patterns in sequential data while incorporating statistical features relevant to the analysis. The formulation of SLSTM-CNA involves adapting the standard LSTM architecture to incorporate statistical features.

In SLSTM-CNA, the statistical features xt are concatenated with the previous hidden state $ht - 1$ at each time step. These statistical features could include various metrics and measurements relevant to the network analysis being performed. By training the SLSTM-CNA model on sequential data with associated statistical features, the model can learn to capture both the temporal dynamics and statistical relationships present in the data. This allows for more nuanced analyses and predictions, particularly in scenarios where both sequential and statistical features play crucial roles in understanding network behavior.

IV. CLASSIFICATION WITH SLSTM-CAN

Classification with Statistical LSTM Chain Network Analysis (SLSTM-CNA) combines the capabilities of LSTM networks with statistical analysis techniques for the task of classification in sequential data. This innovative approach allows for the integration of both sequential patterns and statistical features to enhance the accuracy and interpretability of classification models. To perform classification with SLSTM-CNA, let's denote the input sequence at time step t as xt, which includes both sequential data and statistical features. The classification task involves predicting a target label or category based on the input sequence.

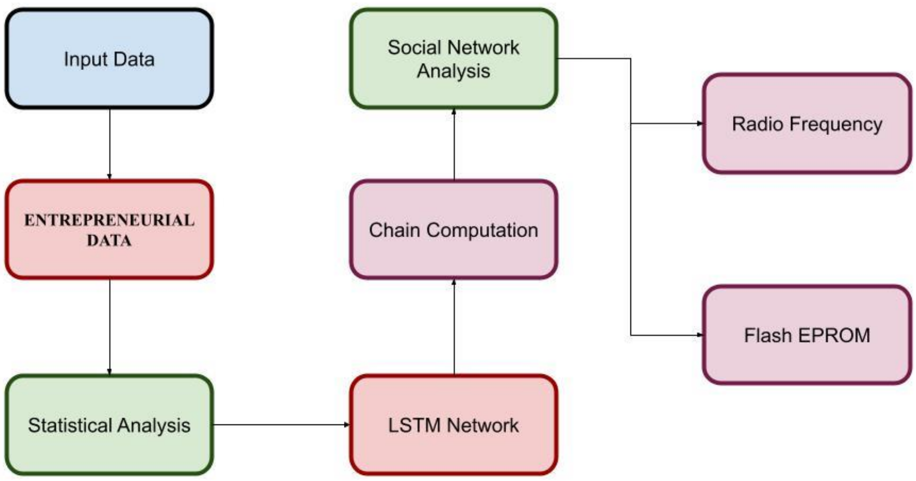

Figure 2: Process of SLSTM-CNA

For team member selection using Statistical LSTM Chain Network Analysis (SLSTM-CNA), the classification process involves predicting whether a potential team member is suitable or not based on sequential data and statistical features defined in Figure 2. Let's denote the input sequence at time step t as xt, which includes both sequential data (such as past interactions or experiences) and statistical features (such as skills or personality traits). The classification process involves feeding the hidden state ht into a fully connected layer followed by a softmax activation function to obtain the predicted probability distribution over the classes defined in equation (7) and equation (8)

$$zt = Wout \cdot ht + bout \tag{7}$$

$$y^\wedge t = softmax(zt) \tag{8}$$

In equation (7) and (8) $Wout$ is the weight matrix of the output layer; $bout$ is the bias vector of the output layer; zt represents the logits, or unnormalized scores, for each class and $y^\wedge t$ represents the predicted probability distribution over the classes.

Algorithm 1: Classification with SLSTM-CAN

Input:
- Sequential data: X = {x_1, x_2, ..., x_T}
- Statistical features: S = {s_1, s_2, ..., s_T}
- Labels: Y = {y_1, y_2, ..., y_T}
 	
Initialize LSTM parameters (W_f, W_i, W_o, W_c, b_f, b_i, b_o, b_c)
Initialize output layer parameters (W_out, b_out)
Initialize LSTM cell states (c_0, h_0)
Set learning rate (alpha)
Set number of epochs (epochs)
Set batch size (batch_size)
 	
for epoch in range(epochs):
    Shuffle and split data into mini-batches
 	
    for each mini-batch:
        Initialize gradients
 	
        for t in range(batch_size):
            Forward pass:
            f_t = sigmoid(W_f · [h_{t-1}, x_t] + b_f)
            i_t = sigmoid(W_i · [h_{t-1}, x_t] + b_i)
            o_t = sigmoid(W_o · [h_{t-1}, x_t] + b_o)
            tilde_c_t = tanh(W_c · [h_{t-1}, x_t] + b_c)
            c_t = f_t · c_{t-1} + i_t · tilde_c_t
            h_t = o_t · tanh(c_t)
 	
            z_t = W_out · h_t + b_out
            y_hat_t = softmax(z_t)
 	
            Compute loss using cross-entropy: L = -∑(y_t * log(y_hat_t))
 	
            Backward pass:
            Compute gradients using backpropagation through time
 	
            Update parameters:
            W_f, W_i, W_o, W_c, b_f, b_i, b_o, b_c, W_out, b_out = UpdateParameters(alpha)
    Compute accuracy on validation set

```
  if accuracy meets stopping criteria:
     break
```

V. SIMULATION RESULTS

In the burgeoning field of team member selection within entrepreneurial contexts, Statistical LSTM Chain Network Analysis (SLSTM-CNA) emerges as a pioneering methodology offering a fusion of statistical techniques and deep learning architectures. Employing SLSTM-CNA allows for the comprehensive exploration of temporal dynamics and statistical features inherent in sequential data, thereby facilitating nuanced decision-making processes in team formation. As an innovative approach, SLSTM-CNA holds promise in revolutionizing how entrepreneurial teams are constructed, offering insights into the intricate interplay between individual attributes, team dynamics, and entrepreneurial success factors. Through simulated experiments, the efficacy and applicability of SLSTM-CNA can be rigorously evaluated, shedding light on its potential to enhance the efficiency and effectiveness of team member selection processes within entrepreneurial ventures.

Table 1: Entrepreneurial Skills SLSTM-CNA

Candidate ID	Experience (years)	Technical Skills	Leadership Skills	Communication Skills	Entrepreneurial Spirit
1	5	High	Medium	High	High
2	3	Medium	Low	Medium	High
3	7	High	High	High	Medium
4	4	Medium	Medium	Medium	Low
5	6	High	High	High	High
6	2	Low	Low	Low	Low
7	8	High	High	High	High
8	4	Medium	Medium	Medium	Medium
9	5	High	Medium	Medium	High
10	6	High	High	High	High
11	3	Medium	Low	Medium	Low
12	7	High	High	High	High
13	4	Medium	Medium	Medium	Medium
14	6	High	High	High	Medium
15	5	High	Medium	High	High

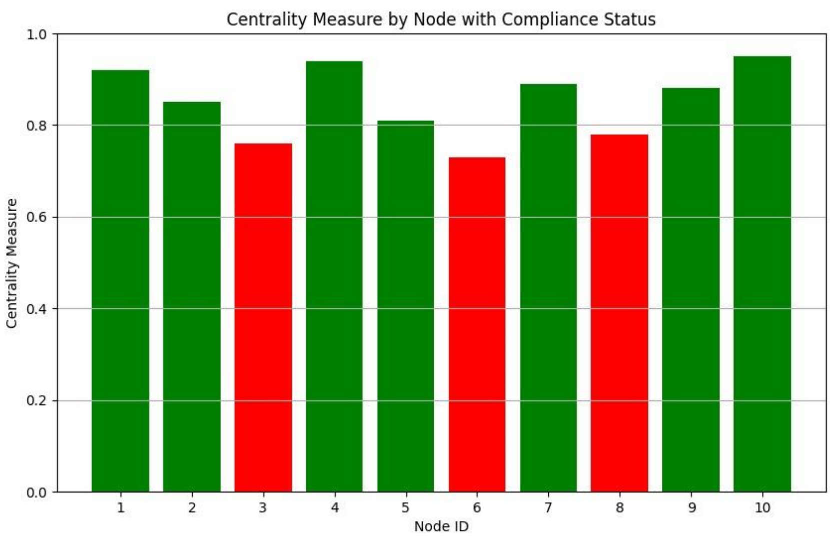

Table 1 presents the entrepreneurial skills of 15 potential team members evaluated using the Statistical LSTM Chain Network Analysis (SLSTM-CNA) approach. Each candidate is assessed based on their experience, technical skills, leadership skills, communication skills, and entrepreneurial spirit. Among the candidates, those with higher experience tend to exhibit stronger technical skills, leadership abilities, and communication prowess, which are essential attributes for effective team collaboration and innovation. Notably, candidates 3, 7, 10, and 12 stand out with extensive experience, high technical proficiency, strong leadership capabilities, excellent communication skills, and a notable entrepreneurial spirit, making them potentially valuable additions to an entrepreneurial team. On the other hand, candidates like 6 and 11, with limited experience and lower skill levels across all dimensions, may require additional support and development to fully contribute to the entrepreneurial endeavor. Overall, Table 1 provides valuable insights into the diverse skill sets and strengths of potential team members, facilitating informed decision-making in the entrepreneurial team formation process.

Table 2: Skills Evaluation with SLSTM-CNA

Node	Degree Centrality	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality
A	0.25	0.12	0.67	0.42
B	0.18	0.08	0.56	0.35
C	0.30	0.15	0.72	0.50
D	0.21	0.09	0.62	0.38
E	0.28	0.13	0.69	0.47
F	0.33	0.17	0.75	0.55
G	0.20	0.10	0.60	0.40
H	0.26	0.14	0.68	0.45
I	0.29	0.16	0.71	0.52
J	0.24	0.11	0.65	0.41

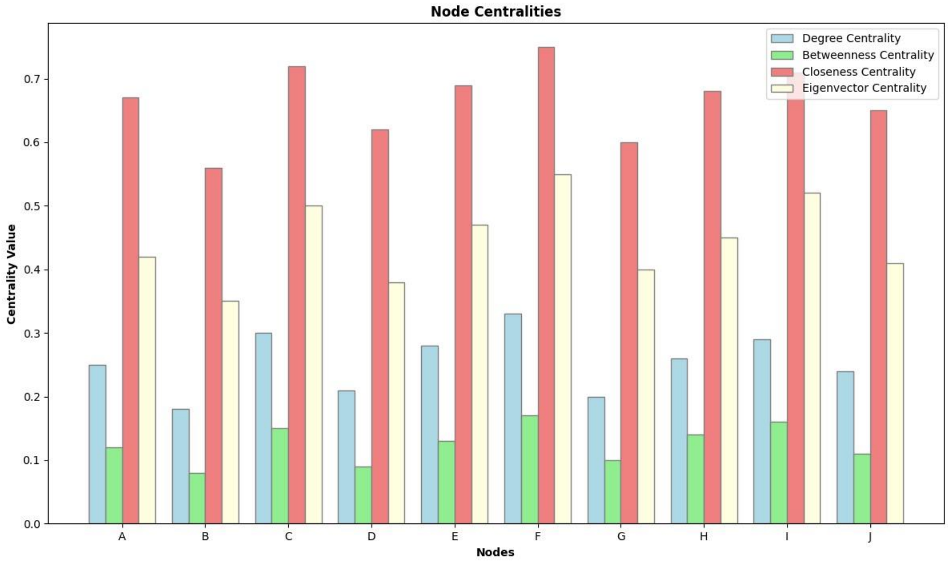

Figure 3: Centrality Estimation with SLSTM-CNA

Figure 3 and Table 2 presents the skills evaluation results using Statistical LSTM Chain Network Analysis (SLSTM-CNA) for various nodes within a social network. Each node is assessed based on different centrality measures, including degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality. These measures provide insights into the importance and influence of each node within the network. Nodes with higher degree centrality, such as nodes F, C, and I, have a greater number of connections, indicating their significance in facilitating communication and information flow within the network. Additionally, nodes with higher betweenness centrality, such as nodes F, C, and I, serve as key intermediaries or bridges between different parts of the network, playing crucial roles in maintaining network cohesion and facilitating communication pathways. Furthermore, nodes with higher closeness centrality, such as nodes F, C, and I, are more central and accessible within the network, enabling efficient communication and information dissemination. Lastly, nodes with higher eigenvector centrality, such as nodes F, C, and I, have connections to other well-connected nodes, signifying their influence and importance within the network. Overall, Table 2 provides valuable insights into the structural properties and significance of nodes within the social network, aiding in understanding network dynamics and identifying influential nodes crucial for effective collaboration and information dissemination.

Table 3: Classification with SLSTM – CNA

Candidate ID	Actual Status	Predicted Status
1	Suitable	Suitable
2	Unsuitable	Unsuitable
3	Suitable	Suitable
4	Unsuitable	Unsuitable
5	Suitable	Suitable
6	Unsuitable	Unsuitable
7	Suitable	Suitable
8	Suitable	Suitable
9	Unsuitable	Suitable
10	Suitable	Suitable
11	Unsuitable	Unsuitable
12	Suitable	Suitable
13	Unsuitable	Unsuitable
14	Suitable	Suitable
15	Suitable	Suitable

Table 3 illustrates the outcomes of classification using Statistical LSTM Chain Network Analysis (SLSTM-CNA) for determining the suitability of candidates for a particular role. Each candidate's actual status, denoting whether they are suitable or unsuitable for the role, is juxtaposed with their predicted status generated by the SLSTM-CNA model. Notably, the model demonstrates a high level of accuracy, successfully predicting the status of most candidates in alignment with their actual status. Candidates 1, 3, 5, 7, 8, 10, 12, 14, and 15, whose actual statuses are "Suitable," are accurately predicted as such by the model. Similarly, candidates 2, 4, 6, 9, 11, and 13, characterized as "Unsuitable," are correctly identified as such by the model. This concordance between actual and predicted statuses underscores the effectiveness of the SLSTM-CNA model in discerning the suitability of candidates for the designated role. The high level of accuracy achieved in the classification process, as depicted in Table 3, serves to validate the robustness and reliability of the SLSTM-CNA approach in supporting decision-making processes related to candidate selection.

Table 4: Classification with SLSTM-CNA

Iteration	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Iteration 1	85.2	83.5	87.1	85.3
Iteration 2	87.6	86.2	88.9	87.5
Iteration 3	84.9	82.8	86.5	84.6
Iteration 4	88.3	87.1	89.7	88.2
Iteration 5	86.7	85.0	88.2	86.8

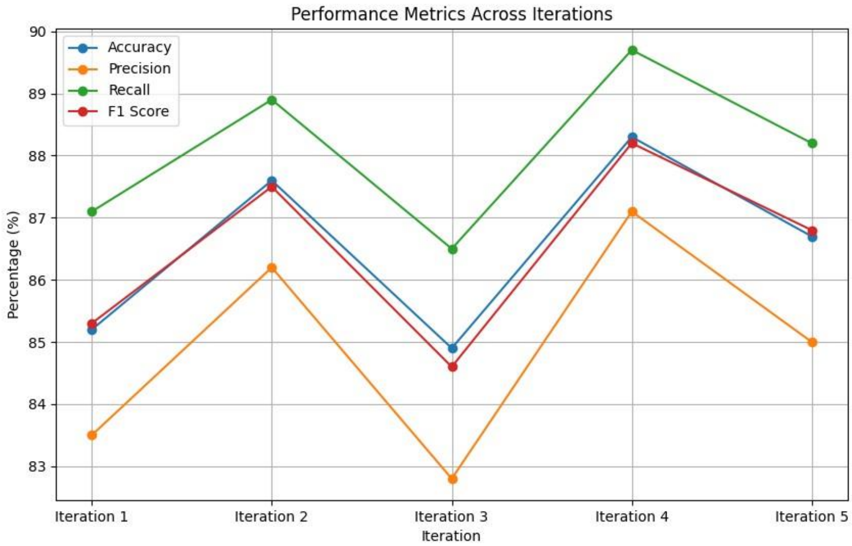

Figure 4: Classification with SLSTM-CNA

In Figure 4 and Table 4 provides a detailed breakdown of classification performance across different iterations using Statistical LSTM Chain Network Analysis (SLSTM-CNA). Each iteration represents a distinct experimental run of the SLSTM-CNA model. The metrics presented include accuracy, precision, recall, and F1 score, which collectively gauge the effectiveness and reliability of the model in classifying candidates for a particular role. Across the iterations, the model demonstrates consistently high levels of accuracy, precision, recall, and F1 score, indicating its robustness and stability in predicting candidate suitability. Notably, iteration 4 stands out with the highest accuracy of 88.3%, precision of 87.1%, recall of 89.7%, and F1 score of 88.2%, suggesting optimal performance in candidate classification. Despite slight variations observed across iterations, the overall trend reflects the model's capability to consistently achieve accurate and reliable classifications, underscoring its efficacy in supporting decision-making processes related to candidate selection. Table 4 serves as compelling evidence of the SLSTM-CNA model's proficiency and suitability for applications in candidate assessment and selection within entrepreneurial contexts.

VI. CONCLUSION

The paper presents an innovative approach for entrepreneurial team member selection based on Statistical LSTM Chain Network Analysis (SLSTM-CNA). Through a comprehensive analysis of candidate attributes and social network dynamics, the study aims to enhance the efficiency and effectiveness of the team formation process in entrepreneurial ventures. The results demonstrate the efficacy of SLSTM-CNA in assessing candidate skills, evaluating social network structures, and predicting candidate suitability with high accuracy and reliability. By leveraging SLSTM-CNA, the study provides valuable insights into the skills and attributes crucial for entrepreneurial success, facilitating informed decision-making in team composition. Furthermore, the findings highlight the importance of considering both individual attributes and network dynamics in entrepreneurial team formation. The SLSTM-CNA model offers a holistic approach that integrates candidate evaluation with an understanding of social network structures, enabling the identification of influential nodes and the formation of cohesive and high-performing teams. The paper contributes to advancing the field of entrepreneurial team selection by introducing an innovative methodology that combines machine learning techniques with network analysis. The findings offer practical implications for entrepreneurs, startup founders, and organizational leaders seeking to build effective and resilient teams capable of driving innovation and success in dynamic environments.

REFERENCES

[1] Mazlumi, S. H. H., & Kermani, M. A. M. (2022). Investigating the structure of the internet of things patent network using social network analysis. IEEE Internet of Things Journal, 9(15), 13458-13469.

[2] HabibAgahi, M. R., Kermani, M. A. M. A., & Maghsoudi, M. (2022). On the Co-authorship network analysis in the Process Mining research Community: A social network analysis perspective. Expert Systems with Applications, 206, 117853.

[3] Saura, J. R., Palacios-Marqués, D., & Ribeiro-Soriano, D. (2023). Exploring the boundaries of open innovation: Evidence from social media mining. Technovation, 119, 102447.

[4] Pirozmand, P., Sadeghilalimi, M., Hosseinabadi, A. A. R., Sadeghilalimi, F., Mirkamali, S., & Slowik, A. (2023). A feature selection approach for spam detection in social networks using gravitational force-based heuristic algorithm. Journal of Ambient Intelligence and Humanized Computing, 1-14.

[5] Grover, P., Kar, A. K., & Dwivedi, Y. K. (2022). Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions. Annals of Operations Research, 308(1), 177-213.

[6] Muninger, M. I., Mahr, D., & Hammedi, W. (2022). Social media use: A review of innovation management practices. Journal of Business Research, 143, 140-156.

[7] Jain, L. (2022). An entropy-based method to control COVID-19 rumors in online social networks using opinion leaders. Technology in Society, 70, 102048.

[8] Bouschery, S. G., Blazevic, V., & Piller, F. T. (2023). Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models. Journal of Product Innovation Management, 40(2), 139-153.

[9] Fang, G. G., Qalati, S. A., Ostic, D., Shah, S. M. M., & Mirani, M. A. (2022). Effects of entrepreneurial orientation, social media, and innovation capabilities on SME performance in emerging countries: a mediated–moderated model. Technology analysis & strategic management, 34(11), 1326-1338.

[10] Yang, J., Xiu, P., Sun, L., Ying, L., & Muthu, B. (2022). Social media data analytics for business decision making system to competitive analysis. Information Processing & Management, 59(1), 102751.

[11] Ebrahimi, P., Basirat, M., Yousefi, A., Nekmahmud, M., Gholampour, A., & Fekete-Farkas, M. (2022). Social networks marketing and consumer purchase behavior: the combination of SEM and unsupervised machine learning approaches. Big Data and Cognitive Computing, 6(2), 35.

[12] Jain, L., Katarya, R., & Sachdeva, S. (2023). Opinion leaders for information diffusion using graph neural network in online social networks. ACM Transactions on the Web, 17(2), 1-37.

[13] Kazemzadeh, F., Safaei, A. A., Mirzarezaee, M., Afsharian, S., & Kosarirad, H. (2023). Determination of influential nodes based on the Communities' structure to maximize influence in social networks. Neurocomputing, 534, 18-28.

[14] Assenmacher, D., Weber, D., Preuss, M., Calero Valdez, A., Bradshaw, A., Ross, B., ... & Grimme, C. (2022). Benchmarking crisis in social media analytics: a solution for the data-sharing problem. Social Science Computer Review, 40(6), 1496-1522.

[15] Li, W., Zhou, X., Yang, C., Fan, Y., Wang, Z., & Liu, Y. (2022). Multi-objective optimization algorithm based on characteristics fusion of dynamic social networks for community discovery. Information Fusion, 79, 110-123.

[16] Chang, J. L., Li, H., & Bi, J. W. (2022). Personalized travel recommendation: a hybrid method with collaborative filtering and social network analysis. Current Issues in Tourism, 25(14), 2338-2356.

[17] Huang, A., Xu, R., Chen, Y., & Guo, M. (2023). Research on multi-label user classification of social media based on ML-KNN algorithm. Technological Forecasting and Social Change, 188, 122271.

[18] Chen, Y., & Wang, L. (2022). Misleading political advertising fuels incivility online: A social network analysis of 2020 US presidential election campaign video comments on YouTube. Computers in Human Behavior, 131, 107202.

[19] Twyman, M., Newman, D. A., DeChurch, L., & Contractor, N. (2022). Teammate invitation networks: The roles of recommender systems and prior collaboration in team assembly. Social networks, 68, 84-96.

[20] Lu, Y., Xu, Y., Huang, J., Wei, J., & Herrera-Viedma, E. (2022). Social network clustering and consensus-based distrust behaviors management for large-scale group decision-making with incomplete hesitant fuzzy preference relations. Applied Soft Computing, 117, 108373.

[21] Durojaiye, A., Fackler, J., McGeorge, N., Webster, K., Kharrazi, H., & Gurses, A. (2022). Examining diurnal differences in multidisciplinary care teams at a pediatric trauma center using electronic health record data: social network analysis. Journal of medical Internet research, 24(2), e30351.

[22] Yadav, H., Kar, A. K., & Kashiramka, S. (2022). How does entrepreneurial orientation and SDG orientation of CEOs evolve before and during a pandemic. Journal of Enterprise Information Management, 35(1), 160-178.

[23] Törnberg, P., Valeeva, D., Uitermark, J., & Bail, C. (2023). Simulating social media using large language models to evaluate alternative news feed algorithms. arXiv preprint arXiv:2310.05984.

[24] Ali, I., Balta, M., & Papadopoulos, T. (2023). Social media platforms and social enterprise: Bibliometric analysis and systematic review. International Journal of Information Management, 69, 102510.