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Original Article

A GNN-Based Framework for Predicting Student Entrepreneurial Success

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Abstract *- In the modern world of innovation, startups play pivotal roles as agents of economic growth, employment, and technological disruption. With learning institutions promoting entrepreneurship, there is an increasing imperative to detect student projects with a long-term potential for success. This research puts forth a predictive framework that applies a high-dimensional set of educational performance, soft skills, behavioral characteristics, and institutional support factors to predict startup success among students. The research compares machine learning models, such as Random Forest, XGBoost, LightGBM, Artificial Neural Networks (ANN), and Graph Neural Networks (GNN), to determine which best represents the complex nature of entrepreneurial success. Interestingly, the GNN model performed the best, with the highest accuracy by successfully learning feature correlations and inter-dependencies. The results have real-world application for universities, incubators, and funding agencies as they facilitate early identification of high-potential student entrepreneurs. This allows for intentional mentoring, focused resource allocation, and the creation of stronger campus-based startup ecosystems.*

Keywords *- Deep Learning, Graph Neural Networks (GNN), Machine Learning, Startup Success Prediction, Student Entrepreneurship.*

1. Introduction

Startups are the key drivers of economic growth, technological advancement, and social innovation in the world today. They create employment, introduce disruptive technologies, and revolutionize industries, making them integral players in a country's economic dynamism and international reputation. In the rapidly changing market landscape we witness today, startups are not merely optional additions to the economy but essential pillars that foster agility, creativity, and resilience [1].

Encouraging students toward entrepreneurship has turned into a strategically important factor because young entrepreneurs typically bring innovative insights, risky suggestions, and a willingness to question long-established conventions. Even with impressive efforts made towards the development of entrepreneurial activity at educational institutions, the proper prognosis of the potential for success in startups created by students remains an intricate and open problem. The survival of an entrepreneur is rarely determined by any single element; rather, it results from an intricate interplay of academic ability, entrepreneurial talent, personality traits such as resilience and leadership, and external factors, such as institutional support and mentorship [2]. Traditional assessment procedures that use qualitative metrics exclusively fail to represent all essential factors that shape students' entrepreneurial path. The failure of traditional assessment methods leads to the potential under-recognition of talented entrepreneurs while resources remain unallocated for talent development.

Artificial Intelligence (AI) has significantly enhanced many areas, including entrepreneurial success predictions by analysing large amounts of data, identifying patterns, and offering insights for better decision-making [3-5]. Despite the advancements, Many existing studies used traditional Machine Learning (ML) techniques, focusing more on organizational aspects by ignoring the key behavioral features related to students. Hence, there is a strong need to use collective features, including essential variables that would enhance the predictive power, such as behavioral traits, psychological attributes, institutional factors and academic achievements.

To address these gaps, this study develops predictive models for student startup success using advanced machine learning techniques. Leveraging data analytics enables more informed decision-making and improves overall efficiency [6]. By applying advanced ML algorithms, predictive modeling helps entrepreneurs estimate future outcomes, offering valuable insights to enhance their performance and strategic planning.

The research employed a comprehensive multi-dimensional database that captures student profiles across various dimensions, including age, academic standing, personality traits, entrepreneurial qualities, and institutional involvement. The complete dataset enables researchers to understand all elements that drive business success.

The study employed various ML techniques like Random Forest (RF), XGBoost (XGB) and LightGBM (LGBM), along with Deep Learning (DL) techniques like Artificial Neural Networks (ANN) and Graph Neural Networks (GNN) for the purpose of startup success prediction. These algorithms were chosen because they consistently perform well in solving classification tasks that involve complex structures and nonlinear feature dependencies.

The GNN model displayed the best predictive results when compared to all other models because of its capability to understand complex data structures. The research findings hold broad significance for various stakeholder groups. The findings enable universities to establish enhanced entrepreneurship learning programs along with better mentorship structures. The predictive model allows startup incubators to identify top candidates for both acceleration programs and investment opportunities. The model helps policy makers and funding agencies optimize their resource allocation by guiding them to invest in individuals with high potential. The research results enable better support for new entrepreneurs through early identification techniques, thus creating more resilient startup systems.

2. Literature Survey

Anitha Gracy et al. compared various machine learning algorithms like Logistic Regression (LR), RF, K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), and XGB to forecast the success of software startups. Their research examined key factors such as the way teams interact with each other and organizational structure, which helped illustrate which algorithms provide better results in forecasting startup success [7].

Ariartha and Rahadian researched the use of machine learning algorithms, LR, RF and KNN to predict startup achievement using Crunchbase dataset information. The analysis indicates that LR outperformed the other models that researchers implemented [8].

Sarisa et al. examined the application of deep learning methods, integrating SMOTE with Recursive Feature Elimination (RFE) and XGB, to forecast the success of software startup firms. Through their approach, the researchers achieved an accurate prediction rate of 90.35% which demonstrates how feature selection and balanced data improve prediction outcomes [9].

Guan et al. introduced a Higher Order Network (HON) model that reflects the interdependencies of investment activities depending on their time of occurrence and order. Through observation of the patterns of information diffusion between investors, their method makes it more accurate to spot winning startups and demonstrates higher accuracy in forecasting future investment patterns [10].

Belgaum et al. had a comparative study of different machine learning algorithms like RF, Gradient Boosting, XGB, and AdaBoost to predict the success of software startups. Their research was aimed at analyzing the performance of these models to verify which methods are most suitable for predicting startup success [11].

Misra et al. created a prediction model based on k-Means clustering and ANN to determine if startups will be successful or not. Their method was 89% accurate, indicating the potential of integrating clustering with deep learning methods for predicting startup success [12].

Shah et al. employed in-depth historical data—like investment rounds, funding dates, milestones, and associated timelines—to create a model to predict startup success. Their methodology demonstrates that examination of previous investment and funding history can accurately predict whether a startup will succeed or fail [13].

Bangdiwala et al. utilized different machine learning algorithms, such as Decision Trees, RF, Gradient Boosting, LR, and MLP Neural Networks, for the prediction of startup success. The model with a 92% accuracy identified how these approaches were efficient for the prediction of startup outcomes [14].

Al Rahma and Abrar-Ul-Haq developed a new theoretical model to predict entrepreneurial success through the integration of five leading theories—Psychological Traits, Human Capital, Social Capital, Institutional, and Resource-Based Theories. With the application of Decision Tree and other machine learning techniques, their research aims at predicting entrepreneurial success in the case of Bahrain [15].

Garodia et al. applied nine machine learning models to classify university students based on entrepreneurial tendencies using academic, demographic, and behavioral data. RF achieved the highest accuracy of 83%, and the use of Local Interpretable Model-agnostic Explanations (LIME) highlighted influential features such as gender, CGPA, study hours, and program involvement, offering interpretable insights to support educational and policy-level interventions [16].

Tahyudin et al. developed a student performance prediction model for entrepreneurship seminar programs using machine learning techniques on limited data. Utilizing the PyCaret library for the full modeling pipeline, the study identified Decision Tree as the most effective algorithm, achieving an accuracy of 98.33% and revealing key performance determinants in various seminar topics [17].

Alam, M. T. and Pradhan, R. P. examined the role of AI and the Internet of Things (IoT) in enhancing Technology Business Incubators (TBIs) to foster entrepreneurial ecosystems. Using a multi-method approach-including descriptive analysis, correlation studies, and regression modeling—the study proposed a predictive and real-time analytical framework that demonstrated high accuracy in forecasting startup success and optimizing resource management within TBIs [18].

Existing models for startup success prediction, especially in the context of student or early-stage entrepreneurs, face particular limitations. The major drawback occurs because these models only assess a small range of variables. Research studies investigate two main types of factors: investment and team-related elements and organizational aspects, but fail to include essential variables influencing student’ entrepreneurial abilities that would enhance the predictive power. The current research landscape demonstrates a lack of deep-learning algorithms that researchers apply. The special techniques needed to understand complex nonlinear data relationships do not exist, which prevents researchers from achieving complete insight into the data and reduces the predictive accuracy of models.

3. Proposed System

The architecture of the proposed work is illustrated in Figure 1. It uses a wide array of features together with sophisticated ML and DL techniques to boost accuracy, psychological aspects and institutional influences. The system provides a comprehensive understanding of student entrepreneurial potential through its holistic assessment approach. The current research utilizes the Academic and Entrepreneurial Development dataset, which contains 214,354 records and 49 different attributes, as shown in Figure 2.
49 features include:

- Student ID
- Age
- Gender
- Major
- Year_of_Study
- Educational_Background
- Socioeconomic_Status
- Location
- High_School_Type
- Cumulative_GPA
- Course_Grades
- Attendance
- Project_Scores
- Internship_Experience
- Applied_Courses_Count
- Club_Membership
- Workshops_Attended
- Competitions_Participated
- Leadership_Roles
- Volunteering_Activities
- Leadership_Skills_Score
- Communication_Skills_Score
- Creativity_Score
- Problem_Solving_Skills
- Risk_Taking_Tendency
- Networking_Skills
- Entrepreneurial_Mindset
- Business_Acumen
- Learning_Style
- Motivation_Level
- Resilience_Score
- Adaptability
- Self_Efficacy_Score
- Mentorship_Hours
- Institutional_Resources_Used
- Faculty_Feedback_Score
- Exposure_to_Entrepreneurial_Curriculum
- Institutional_Support_Score
- Prototypes_Developed
- Startup_Founded
- Funding_Secured
- Business_Plan_Quality_Score
- Competitions_Won
- Research_Publications
- Employment_in_Entrepreneurial_Roles
- Innovative_Skill_Score
- Entrepreneurial_Talent_Level
- Prototype_Completion
- Startup_Success

Among the above 49 features, Startup_Success is a binary outcome variable where 0 indicates a successful student and 1 indicates a failed student.

4. Data Preprocessing

4.1. Label Encoding

The initial data processing stage employed label encoding to transform category-based information into numerical data for the first step of the analysis. The foundation of machine learning requires data to be in numerical form, so this initial process stands as critical for efficient data processing.

Through label encoding, the data became usable for model training purposes since every category received a distinct numerical identification. After applying this approach, the encoded variables could seamlessly become part of the dataset's numerical features that comprised most of the remaining components.

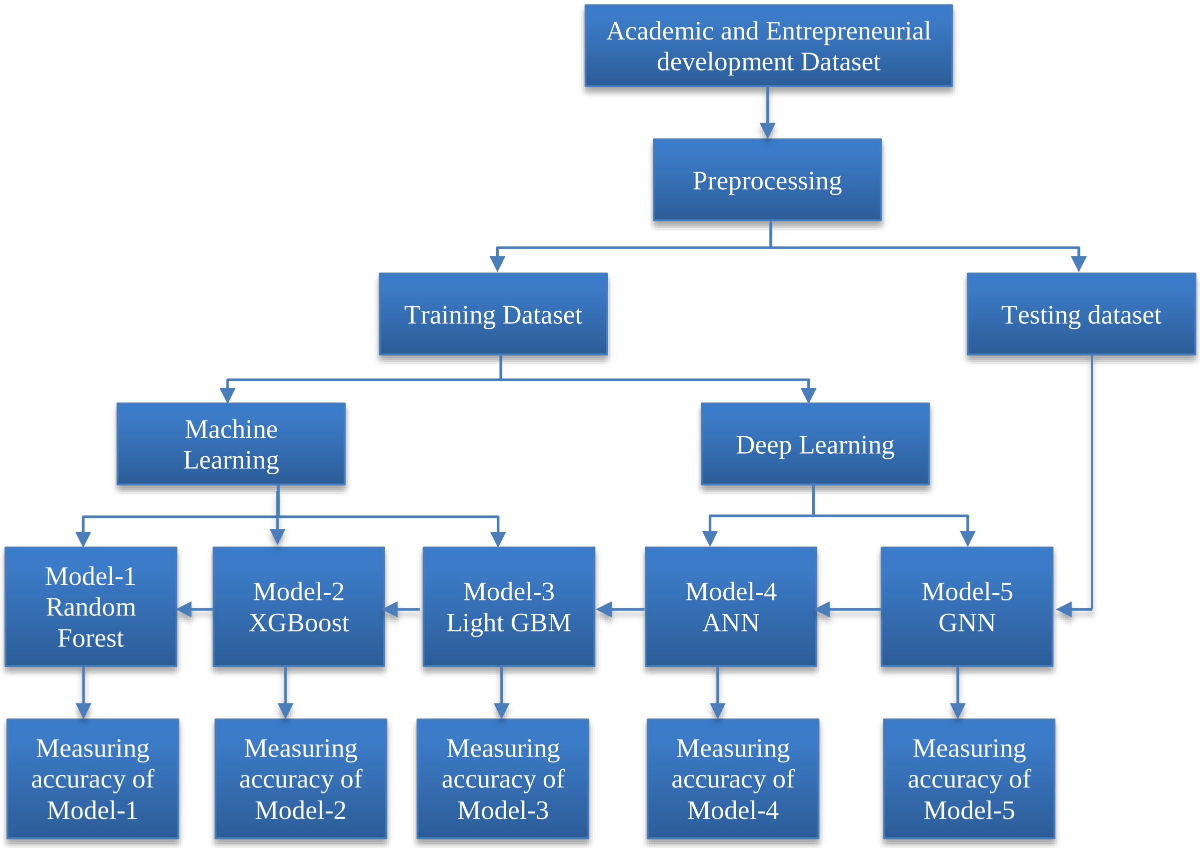

Fig. 1 Architecture of proposed work

```
print(df.shape)
df.head()
```

(214354, 49)

	Student_ID	Age	Gender	Major	Year_of_Study	Educational_Background	Socioeconomic_Status	Location	High_School_Type	Cumulative_GPA	...	Startup_Fou
0	S000001	20	Female	Business	2	Medium	Middle	Urban	Public	1.31	...	
1	S000002	22	Male	Business	2	Medium	Middle	Urban	Public	2.18	...	
2	S000003	21	Male	Sciences	3	High	Middle	Urban	Public	0.26	...	
3	S000004	20	Male	Engineering	4	High	Low	Rural	Public	0.64	...	
4	S000005	19	Female	Engineering	2	Medium	Low	Urban	Public	0.87	...	

5 rows × 49 columns

Fig. 2 Dataset

4.2. Handling Class Imbalance with SMOTE

Studies show that most startups experience failure, according to research conducted by the business community. This trend was evident in our dataset as well, where successful startup cases accounted for only 9% of the total entries, with the remaining 91% representing failures. When the target variable features a major class disparity, the learning performance of the model becomes biased, leading to inaccurate results for minority groups. The Synthetic Minority Oversampling Technique (SMOTE) served as the solution to this issue. By synthesizing new samples from the underrepresented data points through interpolation, this method achieves a better balance in the distribution. The model enhanced its ability to detect successful startup characteristics and improved prediction accuracy as a result. The current dataset includes a total of 3,86,428 records.

4.3. Standardizing Features with Z-Score Normalization

The resolution of class imbalance created a need to achieve consistent scaling for all numerical features in the dataset. Machine learning models would generate biased training results when given data containing attributes with different units and magnitudes, specifically affecting algorithms that require feature scaling. Z-score normalization was the selected method to solve this issue.

The normalization process works by transforming each feature through the mean subtraction and standard deviation division, which establishes a zero-centered data distribution with unit standard deviation. During model training, equal feature contribution occurs because of this normalization process, which improves both learning algorithm convergence and stability. The preprocessing step established uniformity among all features while simultaneously guaranteeing fairness, which resulted in better model performance.

5. Machine Learning Techniques

The dataset is split into two parts: 80% is used to train the model, and the remaining 20% is used to evaluate model performance. In this study, multiple ML techniques, including RF, XGB, and LGBM, are utilized, alongside DL approaches like ANN and GNN. The development and implementation of all models take place through the Python programming language.

5.1. Random Forest

The RF operates as an established ensemble learning technique that functions to address classification and regression challenges. The system creates a "forest" by growing multiple decision trees that it uses for decision-making purposes. The method finds widespread application in practice because of its high precision, effective processing of extensive datasets and capability to handle various data structures. The technique proves to be very beneficial when the relationship between inputs and outputs appears complex and resists explanation through single model approaches. The RF algorithm generates multiple decision trees through the process of training each tree on a different randomly selected part of the dataset. Every tree builds its structure through examining random features at each node, which creates unique variations among individual trees. The three differences between the ensemble models lead to better model reliability, which helps minimize errors originating from noisy or imbalanced data. The ensemble applies a majority voting approach to establish the ultimate prediction by aggregating outputs from every individual tree in the system. The multiple tree approach outperforms single decision trees by delivering improved precision and model strength. Performance metrics of the RF model are presented in Table 1, and the Confusion matrix of the RF model is illustrated in Figure 3.

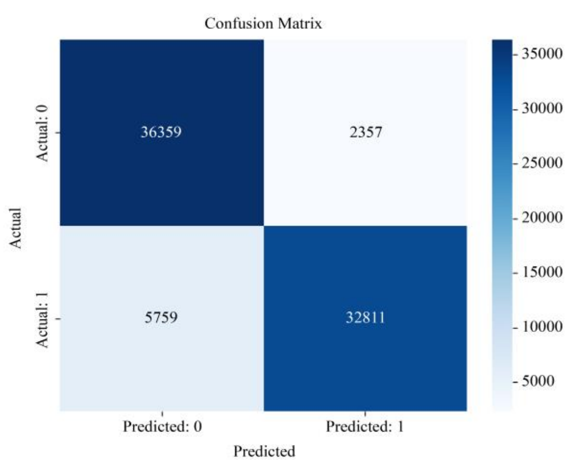

Fig. 3 Confusion matrix of random forest model

Table 1. Performance metrics of random forest model

Accuracy	Precision	Recall	F1 Score
89%	93%	85%	88%

5.2. XGBoost

XGB represents a specially optimized version of Gradient Boosting, which operates as an ensemble learning approach. The model in XGB consists of decision trees as base learners, which the algorithm combines in sequence to improve its performance. Each new tree in the sequence is developed to fix the mistakes that the previous tree made during training.

The XGB algorithm generates decision trees in an ordered sequence by training new trees to correct the inaccuracies of the previous tree. The process begins with an initial plain decision tree-based model, which conducts early predictions. The system then calculates prediction errors by comparing predicted values with actual class labels.

During training, with each successive tree model, the system directs attention toward the incorrect classifications by assigning more weight to these specific data points. The error correction process continues through the addition of new trees, which learn from the faults of earlier trees. In the process of classifying data points, the final decision emerges from the combined predictions of individual trees, which can be interpreted through voting or probabilistic methods.

The iterative nature of XGB enables the algorithm to achieve superior accuracy and dependable performance when handling complex datasets. Performance metrics of

Table 2. Performance metrics of XGBoost model

Accuracy	Precision	Recall	F1 Score
86%	87%	85%	86%

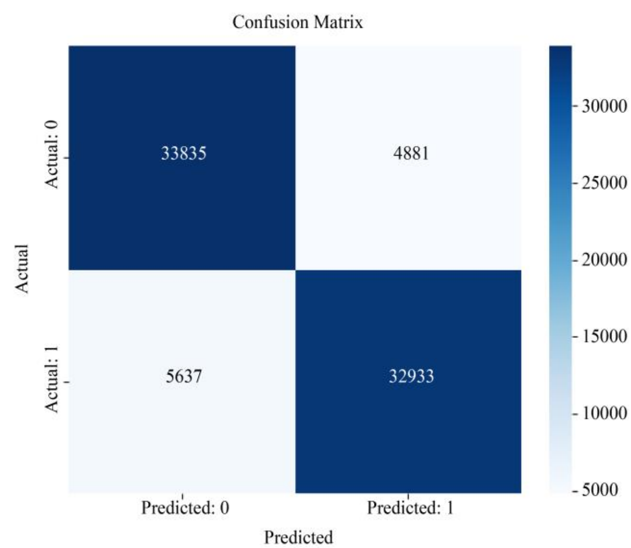

Fig. 4 Confusion matrix of XGBoost model

The XGB model is shown in Table 2, and the Confusion matrix of the XGB model is shown in Figure 4.

5.3. LightGBM

The Light Gradient Boosting Machine, or LightGBM from Microsoft, delivers exceptional performance through its fast and efficient gradient boosting capabilities.

Microsoft developed LightGBM as a machine learning framework for building models that handle classification, regression and ranking problems. This framework delivers better performance and scalability compared to traditional boosting algorithms such as XGBoost when processing large datasets.

The gradient boosting method LightGBM builds decision trees one after another by focusing on mistake correction between successive trees. This method uses a tree-building process different from standard algorithms since it selects the leaf that produces the greatest error reduction for maximum accuracy. This framework naturally supports significant data sizes and categorical input features, which makes it suitable for modern machine learning requirements. Performance metrics of LightGBM model is shown in the Table 3 and Confusion matrix of LightGBM model in Figure 5.

6. Deep Learning Techniques

6.1. Artificial Neural Networks

Table 3. Performance metrics of LightGBM model

Accuracy	Precision	Recall	F1 Score
86%	89%	83%	86%

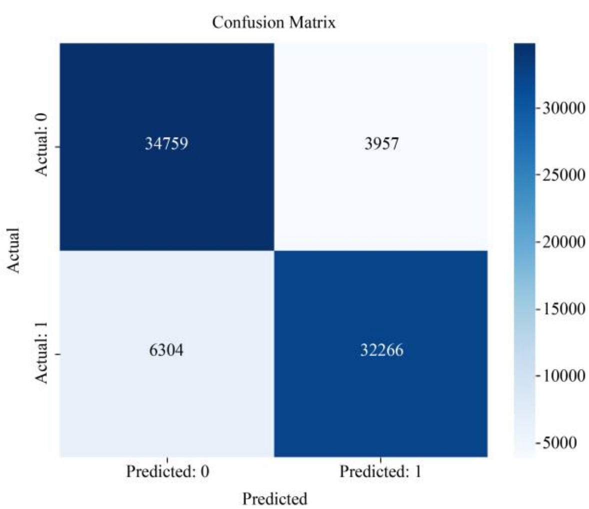

Fig. 5 Confusion matrix of LightGBM model

ANNs use artificial neurons as their basic units. A network exists as a combination of layers that form the complete Artificial Neural Network in any given system. The size of each layer varies greatly because it depends on the number of units necessary for complex neural networks to understand data patterns. ANN normally have three types of layers: the first layer accepts input, and the last layer produces output, while the intermediate layers remain hidden. The neural system processes external information through its input layer before analyzing the data. The hidden layers in the system transform the input data before sending it to the output layer. The ANN produce output responses after receiving input data through its output layer. Neural networks establish connections between layers through unit connections in the majority of implementations. The connection between units contains individual weights that determine how one unit influences the other unit. Performance metrics of the ANN model are shown in Table 4, Training & validation Accuracy over Epochs of ANN model in Figure 6, Confusion Matrix of ANN model is illustrated in Figure 7, Training & validation Loss over Epochs of ANN model is illustrated in Figure 8.

6.2. Graph Neural Networks

GNNs function as artificial networks specifically created to handle graph-structured data through their design. Our study implemented a GNN to predict the probability of student success in startup endeavors.

Table 4. Performance metrics of the ANN model

Accuracy	Precision	Recall	F1 Score
87%	89%	85%	87%

Fig. 6 Training and validation accuracy of ANN

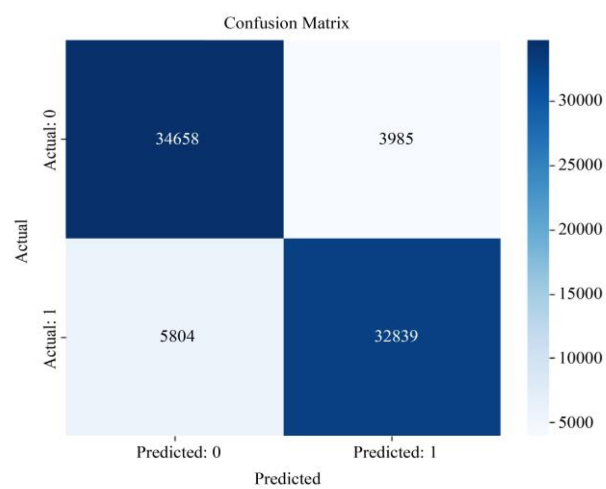

Fig. 7 Confusion matrix of ANN

GNN differs from traditional student analysis methods because it uses individual student features and connections to other students to train the model.

Each student in our system operates as an individual node on our graph. Our process involved connecting each student to their similar counterparts through the K-Nearest Neighbors (KNN) algorithm. We defined these connections as the edges that formed within our graph structure.

The GNN model has a unique framework that operates on input data without direct access to graph structures. Our model constructs the graph through a K-Nearest Neighbors (KNN) algorithm that utilizes student feature vector comparisons. Each student in the network occupies a node position while the system establishes connections between nodes based on their feature similarities to form a topology that reflects local data relationships.

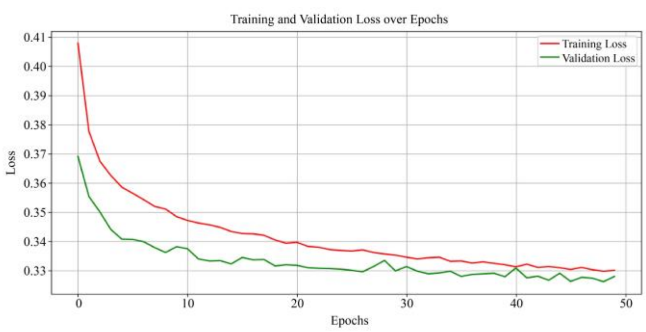

Fig. 8 Training and validation loss of ANN

The process begins by constructing the graph and initializing every node through a multi-dimensional vector that holds important data aspects. Throughout the GNN training process, the model executes an iterative message passing mechanism in which each node collects information from its KNN graph-defined local neighbors. Through the process of message passing, each node gains contextual information from its network through the use of mean or sum operations.

The GNN layers implement learnable mappings to adjust node feature properties, which enhance the model's comprehension of complex structural and feature connections. The network processes student profile details through the combination of individual point features and KNN-based neighborhood patterns.

The model architecture contains four layers, which operate through GCNConv to enable learning between students whose data connections exist within the graph. The model incorporates batch normalization at each layer to optimize training operations while improving speed. The model implements dropout to disrupt memorization since lower data retention helps achieve superior outcomes on new information. Each layer activates through ReLU to encourage the model to learn advanced patterns within the dataset. The model ends its prediction process with a softmax layer that forecasts the success or failure of student startup ventures. We reached a 91% accuracy level through GNN model training involving 100 epochs. The model demonstrates outstanding performance when predicting student startup success. The model continued its learning process through training, so additional epochs could boost its accuracy further.

Table 5. Performance metrics of GNN model

Accuracy	Precision	Recall	F1 Score
91%	90%	92%	91%

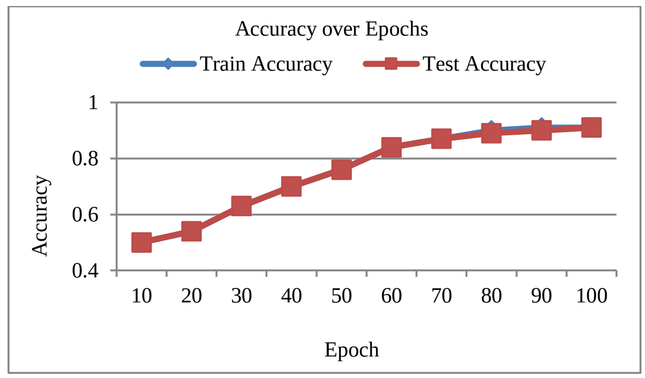

Fig. 9 Accuracy of GNN Model

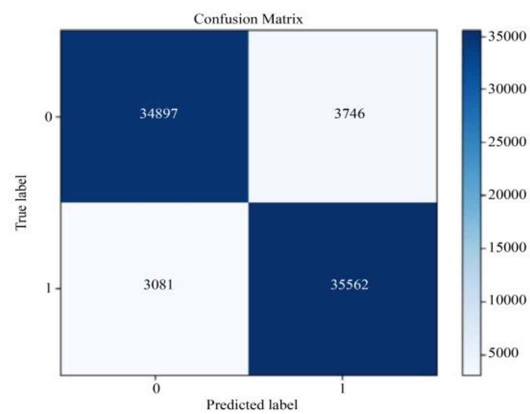

Fig. 10 Confusion matrix of GNN model

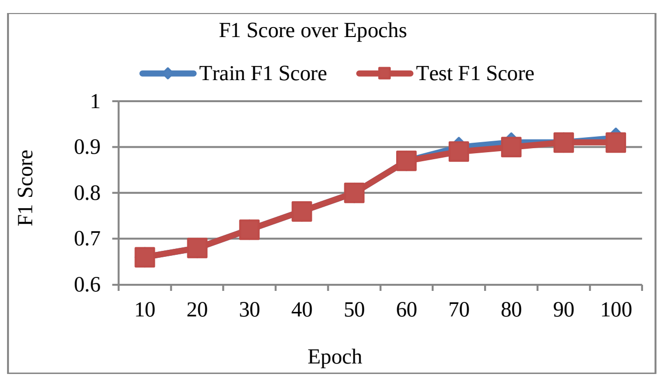

Fig. 11 F1 score of GNN model

The mathematical equation for GNN is

$$H^{(l+1)} = \sigma\left(\widehat{D}^{-1/2}\hat{A}\widehat{D}^{-1/2}H^{(l)}W^{(l)}\right)$$

Performance metrics of the GNN model are shown in Table 5. The accuracy over epochs of the GNN model is illustrated in

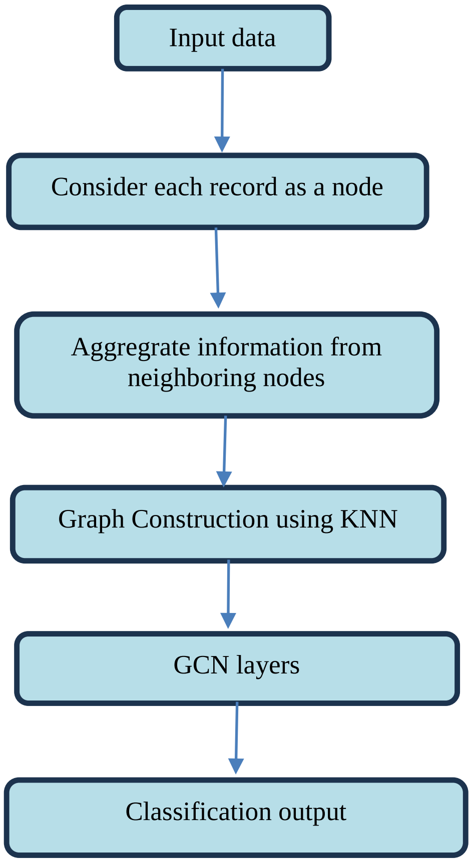

Fig. 12 Architecture of GNN Model

Table 6. Accuracy of all ML/DL models

Model	Accuracy
XGBoost	86%
LightGBM	86%
Artificial Neural Networks	87%
Random Forest	89%
Graph Neural Networks	91%

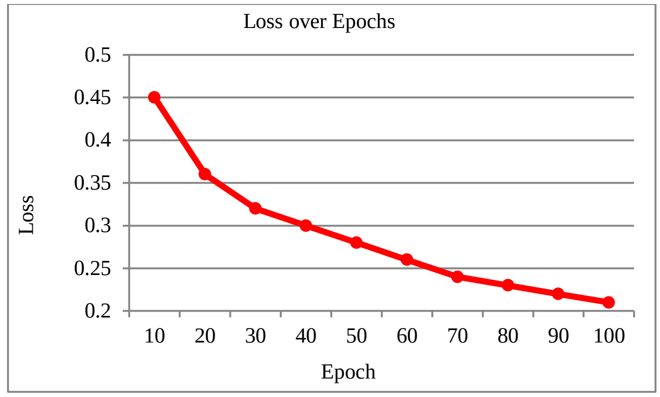

Fig. 13 Loss of GNN model

Figure 9, Confusion Matrix is shown in Figure 10, F1 Score of ANN model is shown in Figure 11, Architecture of GNN model is shown in Figure 12, Loss of ANN model is shown in Figure 13. After applying XGB, LBGM, ANN, RF, and GNN algorithms, the following results are generated, which are shown in Table 6.

7. Conclusion

The present study examines how Graph Neural Networks (GNN) function for predicting student entrepreneurial outcomes based on combined academic, behavioral and entrepreneurial data. The model performs learning through graph construction, which connects students according to their similar characteristics, so it comprehends individual data points and relationship patterns between students.

The evaluation of multiple ML and DL models discovered that the GNN reached the highest accuracy of 91%, which surpassed the performance of RF at 89% and ANN at 87% as well as XGBoost and LightGBM, which scored 86%. The GNN model exhibited superior performance in both accuracy and consistency among all the examined machine learning models. The result demonstrates the specific strength of GNNs in understanding complex data relationships because they excel at modeling structural or interconnected patterns more effectively. Institutions and teachers can use graph-based models to discover students who display high entrepreneurial potential and to deliver early support programs to them. Through this book, AI technology demonstrates its ability to optimise decision-making processes in both educational and entrepreneurial settings.

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