Journal of Industrial and Systems Engineering
Vol. 17, No. 4, pp. 33-48
Autumn (November) 2025

Machine Learning Algorithms for Prediction of Startup Success

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Abstract

Today, startups are turning into the driving forces of the economic growth throughout the world. Large well-known economic companies such as Google, Apple, or recently Airbnb and Uber were initially start-ups that, after the initial stages of receiving capital, greatly affected the world economy and social interactions between governments. During the last decade, number of start-ups has grown dramatically all over the world. The very uncertain and unstable nature of startup environments in the initial stages of their activity has made it difficult to analyze and interpret information in order to evaluate their success. Therefore, investors and venture capital funds need a suitable tool to predict startups' success rate. Considering the time complexity and computationally intensive nature of the problem, predicting startups' success rate at the beginning of their activity with this approach requires the use of a quantitative model. In this study, the success of a start-up company is defined as their ability to reach the next stage of investment within a certain period of time. The ability to predict success is regarded as a valuable competitive advantage for venture capitalists who are looking to invest in startups. In fact, their first choices for investment are companies with faster growth potential than the competitors. Finally, the proposed model enables investors to move one step ahead of the competitors. To address this challenge, the present study provides a solution to predict the startups' success rate in the future. Specifically, first, by collecting the data from three different sources, it examines and extracts factors affecting the startups' success rate. Then, using machine learning methods, it presents a model for predicting the startups' success rate, which has improved significantly compared to the previous models.
Keywords: Prediction, startups' success rate, machine learning.

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ISSN: 1735-8272,

1- Introduction

Given the fact that today many large companies have not been able to achieve innovation and proper progress, the number of startups is increasing and they are attracting a large number of investors. New businesses, or startups, are considered an integral part of the economic prosperity cycle of any society. The presence of uncertainty in their life cycle and a high failure rate of about 90% are among the most important features of startups. Addressing the problem of predicting a startup's success rate first requires having a specific definition of startup success, based on which the methods of predicting their success rate are selected. Various definitions for successful startups have been presented in thematic literature. General and traditional methods for predicting the success of economic companies are implemented based on real data (e.g. sales, production capacity, market size, internal growth, etc.) that is available in the organization. However, due to the requirement for the availability of this type of data, these methods will not much useful for predicting a startup's success rate. Therefore, predicting startups' success rate is difficult due to an uncertainty setting.

Startups, as one of the drivers of progress in today's era, are expected to build a solid system that helps the development of new companies, promotes sustainable monetary development, and expands the range of job opportunities. Through this move, government officials plan to develop new businesses through the development. According to this plan, a number of new startups without work experience and history start their own businesses. However, not all of them succeed, as some cannot survive due to various internal and external business factors and market challenges.

Considering the time complexity and computationally intensive nature of the problem, predicting startups' success rate at the beginning of their activity with this approach requires the use of a quantitative model. In this study, the success of a start-up company is defined as their ability to reach the next stage of investment within a certain period of time. The ability to predict success is regarded as a valuable competitive advantage for venture capitalists who are looking to invest in startups. In fact, their first choices for investment are companies with faster growth potential than the competitors. Our proposed model enables investors to move one step ahead of the competitors.

Machine learning methods are used to discover hidden patterns through analyzing based on data-oriented programming. Using these practices, different applications can be developed to support different business sectors. Managers and business directors will use these patterns for sustainable development, growth and resistance to global business challenges. In this context, the use of machine learning methods in business data analysis can become a useful tool to help startup businesses and new entrepreneurs to survive and grow over time.

Therefore, this study aims to investigate machine learning methods that have recently helped to understand the needs of startups, improve business processes, and can provide recommendations for planning their future strategies to deal with business problems. Then, based on the observations, it proposes a future roadmap for designing and developing an intellectual framework to support startup entrepreneurs located in Iran.

Considering the fact that today many large companies have not been able to achieve innovation and proper progress, the number of startups is increasing and they are attracting a large number of investors. New businesses, or startups, are considered an integral part of the economic prosperity cycle of any society. The presence of uncertainty in their life cycle and a high failure rate of about 90% are among the most important features of startups (Ghikas et al., 2019).

Addressing the problem of predicting a startup's success rate first requires having a specific definition of startup success, based on which the methods of predicting their success rate are selected. Various definitions for successful startups have been presented in thematic literature. General and traditional methods for predicting the success of economic companies are implemented based on real data (e.g. sales, production capacity, market size, internal growth, etc.) that is available in the organization. However, due to the requirement for the availability of this type of data, these methods will not much useful for predicting a startup's success rate. Therefore, predicting startups' success rate is difficult due to an uncertainty setting. It is essential for startups to assess whether they are on the path to success or not. Startups' failure rate in 2019 was about 90%, making it necessary to understand their success rate.

The first goal of this study is to use the investment network in order to obtain more effective features, based on which a machine learning model for predicting the startups' success rate is developed. This machine learning model is built by extracting effective features through investment graph analysis and using these features along with the other data in the dataset of the startups and investors. The second goal is to select an effective machine learning model for accurately predicting the startups' success rate according to their features.

2- Literature Review

Despite the variety of available definitions for the concept of *startup*, most of them agree on one point: startups are designed for rapid growth. This definition is consistent with Paul Graham's definition, who says "the very essential point in defining startups is growth, everything else we associate with startups comes from growth". Unlike Graham, Peter Thiel believes that startups are fundamentally about development of technological innovation. He explicitly refers to vertical innovation, which means the development of a new technology that has not been created before, as opposed to horizontal innovation, which involves bringing existing technologies to new locations. Every startup is a fledgling company run by at most a small group of people. Startups enjoy a good growth potential, as they can offer new value to the customer through a previously unknown product or service.

Although startups are often associated with technology (as Peter Thiel's definition implies), this is not always the case. The primary use of this term (late 1970s) was explained by the rapid growth of technological advances at that time and the subsequent explosion of the Internet (in 2000) [Startup Commons, 2019]. Today, having high technology is not a condition to be recognized as a startup; rather, a startup can be, for example, an organization that creates an advanced manufacturing method (based on technology) as well as an e-commerce platform for direct purchase of products from farmers (enabled by technology). As Graham mentioned, the only essential point is *growth*.

According to the definition provided by Techleap.nl, which is an investment platform for startups in the Scandinavian countries, a startup in an ecosystem is not a service provider, not a subsidiary of a larger company, and has more than 1 employee, and does not have an age of less than 20 years old. Startup Delta does not provide a clear definition of the company size according to the number of employees. According to their definitions, startups with individual founders, as well as startups with an age of more than 20, are not included in the definition of a startup. Moreover, the boundaries should be specified in terms of the number of employees and the age of the organizations. In terms of age, if the age of an organization is less than 10, it can be recognized as a startup.

In terms of the number of employees, the Organization for Economic Co-operation and Development (OECD) has provided the following classification for micro-, small-, and medium-sized enterprises: micro-sized enterprises has less than 10 employees, small-sized enterprises has 10-49 employees, and medium-sized enterprises has 50-250 employees.

Now let us investigate the question of what is the difference between startup and small and medium-sized enterprises (SMEs). According to the previous definitions, a startup is designed for rapid growth and is associated with a large value of uncertainty.

Unlike startups, SMEs experience a slow and stable growth throughout their life cycle. Startups are often funded by risk-taking investors such as angel investors and venture capitalist (VC3), while SMEs are funded by more risk-averse options such as bank loans. The probability that SMEs will survive after two years is 75%, while for startups this probability is 25% [Compass, 2015]. In startups, the risk is high, but there are rewards as well. Let us do a comparison between a small business and startups. Your local ice cream shop will probably never become a billion dollar enterprise creating thousands of jobs, while a successful startup has a better chance of achieving that goal. What is the relationship between entrepreneurship and startups? Although the founder of a startup is an entrepreneur, the founder of a local ice cream shop is considered an entrepreneur as well. Contrary to the initial definitions of entrepreneurship concepts, while it seems that innovation is in the nature of an entrepreneur, today an entrepreneur is a person who performs entrepreneurial activities by creating new jobs.

3- Emergence of Startups

Human has now passed the tipping point between the industrial and information ages. In the last 50 years, blue-chip companies have lost their dominance, becoming vulnerable to new entrants. In the industrial age, blue-chip companies were protected by low levels of competition, information darkness, and ever-increasing consumption. The information age made these barriers obsolete. Today's technologies bring about more transparency in creating new jobs and information. Considering the increasing importance of economizing and being aware of the environment, new consumers have also moved towards the sharing or rental economy. Startups are also increasing due to the inability of large companies to advance in the field of innovation and match the emerging trends. Photography was made obsolete by Instagram, bookstores by Amazon, music by Apple and Spotify, chained-brand hotels by Airbnb, taxis by Uber, traditional human resources by

LinkedIn, newspapers by social media, and retail stores by e-commerce. Although startups may be highly profitable, they are always associated with a significant risk. Despite the 90% failure rate of a startup, why do we see the emergence of startups everywhere? In his book titled "The Four Steps to the Epiphany", Steve Blank mentions four reasons for this phenomenon: 1) Startups can now be built by thousands of people, but for millions; 2) New investors with smaller checks (e.g., angel investors, accelerators, micro VC investors); 3) New management science for startups; and finally, 4) Faster adoption of new technologies by consumers, for example due to a more connected and globalized society. Unlike blue-chip companies, the number of startups is increasing. What does this mean? Why are there startups? First of all, startups play a very vital role in advancing economic and job growth. In fact, today's economy is directed by the most successful tech startups like Facebook, Google, and Amazon. In the next decade, the global economy will most likely have major players, of which the reader has never heard; they may not even exist yet. Startups grow at a higher speed and create significant disruptions in the global economy. Beyond generating income, startups enhance employment, as a large number of them create jobs (Abdi et al., 2025). In fact, over the past 28 years, "startups have been responsible for the creation of net new jobs in the United States." Startups have also helped reinvent power structures. We are transitioning to a society where power is shared and governed by many people. Therefore, a new set of values has been created based on participation, among which informal decision-making, network governance, open source collaboration, fundamental transparency, automated culture, and short-term dependence can be mentioned.

In this section, we review a summary of Persian and foreign research related to the research topic: Yavari Gohar et al.(2019) and Abdi et al., (2025) in their study identified and prioritized the factors affecting success and failure of tourism startups in Iran. The aim of the present study is to identify and prioritize the success and failure factors of tourism startups located in Iran using another methodology different from theirs. To this end, the available literature and other researches conducted by domestic and foreign researchers were studied and a researcher-made semi-structured interview was performed. Then, using the purposive sampling method in qualitative research, the research sample was selected out of the owners of the tourism startups located in Iran. Finally, using the qualitative content analysis method, the factors affecting the success and failure of tourism startups were identified in 10 main categories. Then, using the Shannon entropy method, which is derived from systems theory, the priority of each 10 identified categories in the success and failure of the tourism startups was determined based on the weight of the data. According to the results, the factors affecting the success of startups include human resources, organizational factors, product/service, customer/market, competitive factors, financial resources, technological resources, legal political factors, economic factors, and unpredictable factors, respectively. Also, the priority of factors affecting the failure of these businesses include political, legal, unpredictable factors, organizational factors, human resources, customer/market, financial resources, economic factors, competitive factors, product/service and technological resources.

In a case study conducted by Noor Mohammad (2020) on health startups, the key factors affecting the success of startups were identified and prioritized. By reviewing the literature, asking opinions, and interviewing the experts, in this research, the key success factors of startups in the field of health were identified and selected by the screening method, and the questionnaire was designed and completed by the experts. Analyzing the data using the Fuzzy DEMATEL method in Excel software showed that “effective human power” is the most influential factor and “strategy and policy making” is the most influencing factor. Moreover, the solution with the fuzzy ANP method indicated that the highest weight is related to the criterion of “skilled manpower”, winning the first priority.

Kim et al. (2023) predicted the success of a startup using a machine learning approach. Predicting startups’ success rate is a critical task for entrepreneurs and startup investors. A machine learning model incorporating industry features was developed to predict the success of a company. The data was collected from 218,207 companies on Crunchbase from January 2011 to July 2021. After data preprocessing, six machine learning models were used to predict the startups’ success rate and identify important features for prediction. Feature importance was also calculated to determine how each feature affected the prediction of the startups’ success rate.

Bhaskar et al. (2022) in a research using an experimental approach based on machine learning techniques determined the essential features to predict startups’ success rate. The important features derived from this approach show how entrepreneurs prioritize the determinants of startups’ success rate and maximize socio-economic outputs. The current study significantly contributes to the entrepreneurial finance literature by empirically investigating the features affecting the success of a startup based on its financial performance at different stages of its life cycle. Startups can apply the implications of this study to reduce their uncertainty and increase their performance. It also helps founders, investors, and researchers to understand the performance of a startup and plan future steps accordingly.

In their study, Malhar et al. (2022) predicted the startups’ success rate using machine learning algorithms. The models used include: decision tree, random forest, gradient boosting, logistic regression, and MLP neural networks. The data used to train these models includes key features such as valuations, funding rounds, investments, etc. By using the mentioned models, the company's path can be estimated. After applying the models, a precision of about 92% in all of them can be achieved. This information will be vital to the company's various stakeholders as well as potential investors.

4- Research Implementation Method

In this section, the steps for the quantitative implementation of the study are presented. Inspired by the previous studies that have used hybrid methods, in this thesis, a hybrid method is considered to predict the startups’ success rate. To this end, a combination of network analysis method and intelligent machine learning method is used to build a startup success prediction model. These two methods are illustrated in two different phases in Figure 1. The network analysis phase is actually the statistical part of the study and the machine learning phase is the intelligent part. Most of the previous studies have directly used the features in the datasets of startups and investors. In this thesis, the new features resulting from the analysis of the investment network between startups and investors are used, along with other features, and this is the main innovation of this thesis. Ensemble learning methods are also used in the machine learning phase.

The implementation steps of the study include two main phases: machine learning and network analysis. By using the dataset of the startups and investors as the input of the network analysis phase, the investment network with a graph nature is formed. By analyzing this graph, we get the features that are effective in predicting the startups' success rate. In fact, these features are used along with the other data in the dataset of the startups and investors to build a machine learning model.

The activities taking place in the dataset pre-processing phase include:

- Data cleaning
- Data enrichment
- Data transformation
- Data normalization

In many data sets, there are problems that should be fixed in the data preprocessing phase, among which wrong data with wrong format, empty values, and wrong placement of information can be mentioned. In order to increase the model efficiency, the data containing these errors are excluded from the data set. In the enrichment phase, new columns, e.g. columns with network feature values, are created from the features extracted in the investment network analysis phase.

In the transformation phase, the one-hot encoding method is used to transform the categorical data into the numerical data. Also, in order to increase the model precision in predicting success, the classes related to the tag of startups are reduced from 5 unicorn classes (stocks listed in the share market, stocks purchased, congoing activity, and exited from activity) to 2 classes (success and failure), and are finally converted into the binary form (0) and (1). We designate the first three tags as startup success, and the two tags related to congoing activity and exited from activity method is used.

5- Investment Network Analysis

In order to use the features of the investment network in building a startup success prediction model, a two-part graph of startups and investors should be formed and for each startup and investor node, the feature values should be found. The features related to the investment network include: degree of centrality, degree of betweenness, and degree of closeness.

The greater the number of investors (connections of a startup in the investment network), the more important that startup is in the network. In other words, the startups are ranked based on the number of their connections. Moreover, instead of considering the nodes themselves in the investment network, the betweenness criterion considers the structure of the network to identify important startups in the network. In the investment network, the neighbors of a startup are the startups that have a link or connection to the startup in question.

After finding the values of these features for each node in the startup-investor graph or the same graph resulting from the investment network, we add them to the main data set and complete the data enrichment phase. In this phase, the form and the way in which the startups and investors communicate can be depicted. This phase can be considered the most important part of this study. As mentioned earlier, one of the innovations of this study is the use of new features and the investigation of their effectiveness. It should be noted that the output of network analysis is a set of features related to the network that are added to the pre-processed data set and will be considered as data enrichment.

6- Findings

For proper data analysis and model building, the should must be fully prepared. Data preparation consists of several sub-processes including data cleaning, enrichment, and transformation. Using the Pandas library embedded in Python, we incorporate 4 raw data set files and produce a unified data set. The row related to the missing data is excluded. In addition, the columns with no effect on the success of startups, e.g., those containing the website link of startups and investors, or the code of the place of birth of startups, are excluded from the data set. After the initial pre-processing steps, a file in CSV format with the following columns is generated: startup name, startup industry classification, the amount of investment received by the startup, and the current status of the startup.

The features affecting the startups' success rate were present in the data extracted from the Crunchbase website. Too many of these data have wrong and missing values. As a result, the output of the initial preprocessing consists of a unified file containing 10,435 startups with the above information and features.

Moreover, in the current status part, the raw data set includes 5 tags of stocks purchased, listed in the share market, and unicorn for success, and ongoing and exited for failure. In order to increase the precision and efficiency in the data set for use in the prediction model, we convert these 5 classes into two success and failure classes and take the problem to the binary classification solution space.

Another part of the data preprocessing process is related to the conversion of startup industry categories from categorical to numerical. To this end, the one-hot encoding method is used. In this method, instead of categorizing startups by industry, which have non-numerical values, we convert them to numerical values 0 and 1, i.e., for each startup, columns of all the industry fields that are available in the data set are formed, and the industry column of each startup that is present in that category is entered as one, and the rest of the other industries column of that startup is entered as zero.

7- Network Analysis

In this phase, after analyzing the investment network on startups, the features of the network are extracted by using the Gephi software and the dataset produced in the previous phase. In this software, we build a two-part graph resulting from the relationship between startups and investors, in which nodes indicate startups and investors, and edges indicate investments on startups by investors. For each node, the features of the network, including degree of centrality, PageRank centrality, eigenvector centrality, closeness centrality, and betweenness centrality, are extracted. After calculating the values of these features for each of the network nodes, they are added to the main data set in separate columns. This part is introduced as the final pre-processing in the research flow chart.. After preparing the data set, two separate data sets are extracted under the titles of:

- Data set without network features
- Data set with network features

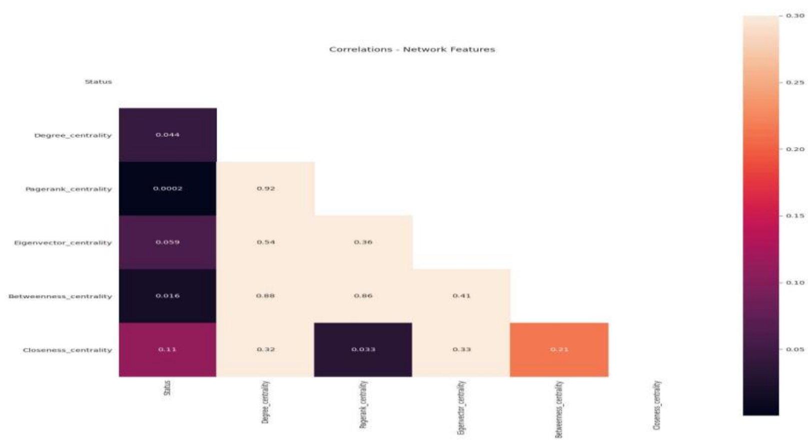

Figure 1. The degree of correlation among investment network features.

Moreover, the degree of correlation for all the features of the pre-processed data set, including the main and network features, is presented in Figure 2.

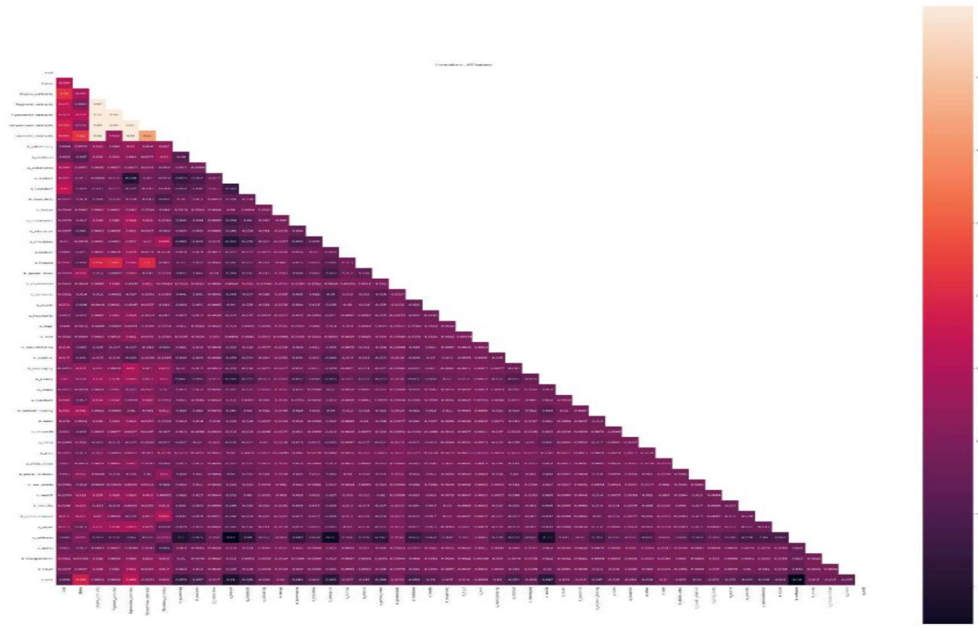

Figure 2. Degree of correlation of all the features in the pre-processed data.

In this figure, each square is an intersection of two features, inside which the value of the correlation coefficient between them is written. The darker the color of the square, the closer the correlation between the two features is to zero, and the lighter the color, the closer this value is to one. In this set, the features with a low correlation coefficient with each other and independent of each other are selected as influencing. Moreover, as shown in the figure, due to the low correlation value of the features together, all of them are selected for use in building the model.

After calculating the degree of correlation among the features and choosing the set of influencing features, the selected algorithms to build the prediction model are coded in the Python environment. In this section, the output results of ensemble learning (LGBM), random forest, and support vector machine algorithms are compared. After determining the value of the variables and metavariables of each algorithm and testing them, the level of precision, the level under the ROC curve (AUC), and the confusion matrix are presented for the selected algorithm. In addition, in this step, the effect of the network features on the results of the algorithms is evaluated.

8- LGBM Algorithm

As an ensemble learning algorithm, the LGBM is expected to achieve better results than the others. After determining the value of the variables and meta-variables of this algorithm and running the program, the results are obtained. Also the output of the confusion matrix for this algorithm in the mode of not using network features is presented in Figure 3.

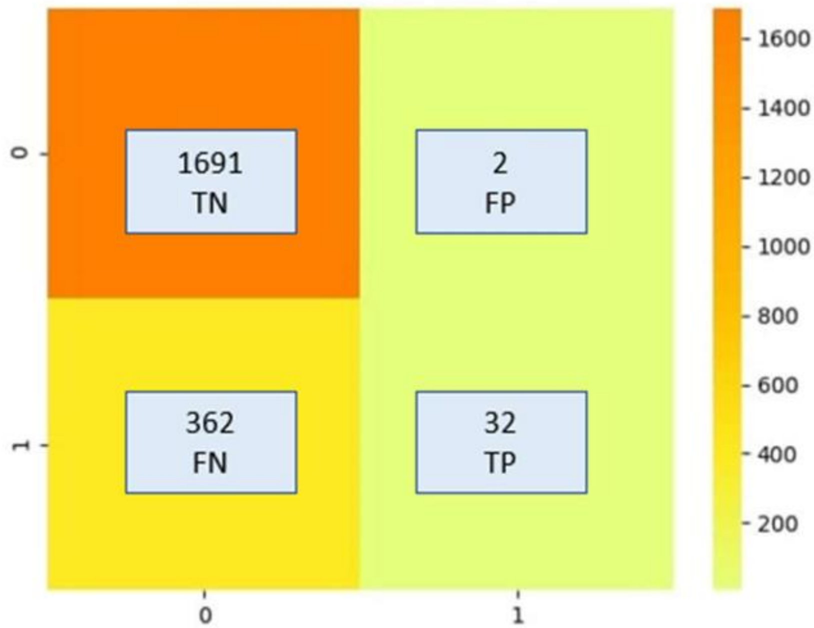

Figure 3. Confusion matrix of LGMB algorithm in the mode of using network features.

As can be seen, the number of correct predictions of success has increased from 7 startups to 32 startups. Moreover, the success predictions have decreased from 5 to 2. This performance improvement is also noticeable in predicting failed startups. Now, by comparing the AUCs for different startups, it can be seen whether the use of network features has affected the predicted performance of the model or not. Figure 4 shows the ROC curve for the LGBM algorithm in the case of not using network features.

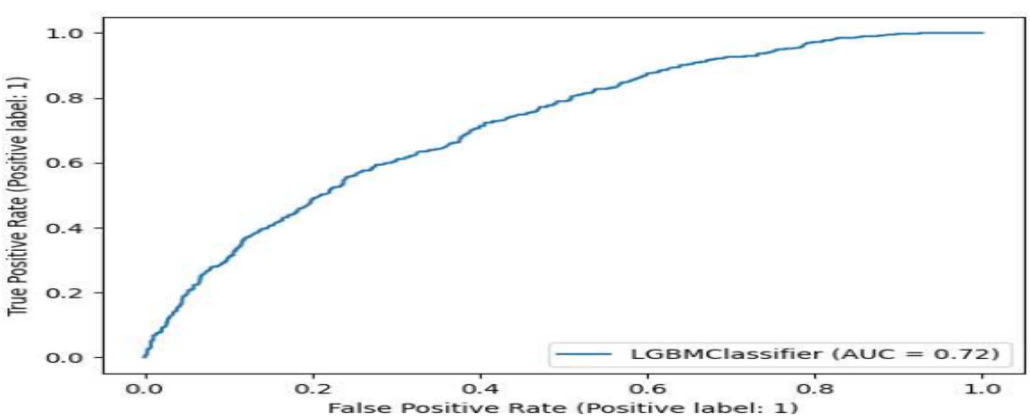

Figure 4. ROC of LGMB algorithm.

In Figure 4, the AUCs are plotted in the case of not using the network features, and in this figure, the ROC values are also obtained for different thresholds of the success probability.

This value is equal to 72% in the case of not using the network features, but in Figure 5, the ROC diagram is obtained for the case of using the network features in the model training phase.

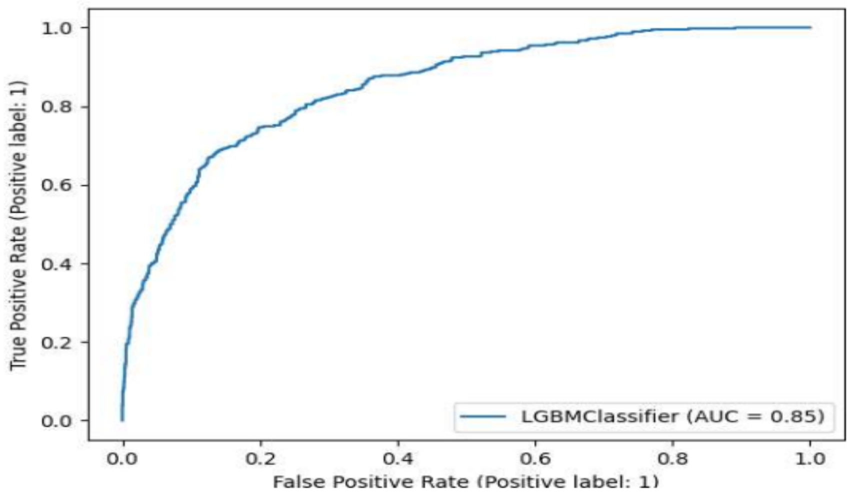

Figure 5. ROC diagram of LGMB algorithm in the mode of using network features.

After determining the metavariables of the support vector machine algorithm, e.g. the width of the Gaussian kernel, the algorithm is executed with the Fold Cross Validation-10 method, and in the test phase of the algorithm, the results are presented in the modes of using network features and not using them in the model training phase. The results of the ROC curve in the mode of not using the network features are illustrated in Figure 5. As it can be seen, the SVM algorithm has shown a poor prediction performance and the AUC value for this algorithm in the mode of using network features is 52%, which is close to the prediction using random forest algorithm.

Although the use of network features has a positive effect on the prediction of the algorithm, this effect is insignificant.

9- Conclusion

In this study, after implementing the stages of building the startup success prediction model, the numerical results of each stage were presented. By comparing the used algorithms, the Light Gradient Boosting Machine algorithm was selected as the best algorithm to predict the startups' success rate. Moreover, the use of network features had a positive effect on the performance of the model and machine learning algorithms. However, as mentioned in previous studies, due to the fact that the chance of accurately predicting startups' success rate is still low, there are gaps to be filled by conducting future research in this field.

Startups are of special importance as an integral part of the economic and technological environment of any country. Since a high percentage of startups have failed and there are many uncertainties in their life cycle, prediction of their success rate is critical. By predicting the future of startups, it is possible to prevent many expenses that may harm their beneficiaries and make the path of successful investment in this field smoother.

In response to the first question, it should be said that the network resulting from the relationship between investors and startups has features, each of which can somehow indicate the importance of a startup within the investment network. The importance of a startup in the investment network can significantly affect its success.

In this study, we found a set of features by analyzing the investment network, one of which is the centrality degree of a startup in the investment network. The greater the centrality degree of a startup, the greater the importance of the startup in the network and the more relevant it is for investors as well as the more chances of investing in it. This, in turn, can increase the startups' success rate. The other features, as discussed in detail in chapter 4, show the degree of significance and influence in the network.

In response to the second question, it can be said that the use of ensemble learning algorithms in this case study gave rise to better results. Among the three algorithms used to predict startup success, the LGBM algorithm was selected as the best algorithm in terms of precision and AUC value. In addition, the use of the features of the investment network had the greatest impact on the results of the LGBM algorithm.

The answer to the third question is also positive, as the use of network features in the three algorithms used to predict the startups' success rate increased the precision. For example, when using the network features in the training of the LGBM algorithm, the prediction accuracy of the algorithm increased greatly. As mentioned in chapter 5, the use of network features in the LGBM algorithm improved the accuracy rate by 36%.

Providing a method for prediction of startups success rate can be mentioned as the most important achievement of this thesis. Another achievement of this study is the measurement of the effect of network features on the results. The output of this research plays a key role in helping investors and founders of startups and accelerators, as predicting the startups' success rate makes them able to choose the best investment policies and planning to improve the factors influencing their success. In this way, investors can invest in startups with less risk.

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