© April 2025 | IJIRT | Volume 11 Issue 11 | ISSN: 2349-6002

Startup Profit Prediction Using Informational Resources

Shruti Banchhod[1], Om Suryawanshi[2], Akhouri Ayush Kumar Sinha[3], Asmit Upganlawar[4], Prof. Vanita Gadekar[5]

[12345] *Department of Computer Engineering, Smt. Kashibai Navale College of Engineering, Pune, India*

***Abstract*— Machine learning techniques are used for discovering the hidden patterns from the application-centric data analysis. Using these techniques various applications can be developed which can be used for supporting different business sectors. These patterns will be used by business administrators and managers to develop sustainable, growing, and withstand the global business challenges. In this context, the employment of machine learning techniques in business data analysis can become a fruitful tool that can assist and help to new start- ups businesses and entrepreneurs, to sustain and grow with time. Therefore, in this paper, we are conducting a review on existing machine learning techniques that are recently contributed to understand the need of start-ups, trends of business and can provide recommendations to plan their future strategies to deal with the business problems. Secondly, based on the observations we have proposed our future road map to design and develop an intellectual framework to support Start-up India-based entrepreneurs.**

***Keywords*—Machine learning, recommendation system, business data analytics, algorithm design, support system, handholding of startups.**

I. INTRODUCTION

Startup India is a drive of the Government of India, expected to fabricate a solid system that will helpful for the development of new companies, to drive maintainable monetary development, and produce scope of job openings. Through this drive, the public authorities plan to engage new businesses to develop through advancement. A few projects have been attempted since the launch of January 2016 by the Prime Minister [1]. Due to this program, a number of new start-ups without any business background and experience start their startup business. But not all of them got success some of the start-ups are failed to survive, due to various internal and external business factors and market challenges. On the other hand, Manufacturing is a worldwide influenced with the implantation of digitization and is in a progress stage moving from physical to digital frameworks with the appearance of Industry 4.0. Industry 4.0 is the latest thing of computerization and information trade. It incorporates digital frameworks, the Internet of things, and cloud computing. It is significant for us to prepare for the future by receiving a few progressed patterns to change the assembling scene. To tap the chances FICCI has taken up a drive to establish a board of trustees on Industry 4.0. This board means to zero in on making mindfulness about this new innovation and furthermore support the Government in fostering a guide for the business [2].

Therefore, in this paper, we proposed an intelligent framework using Machine Learning (ML) technique for supporting the new startups and entrepreneurs to deal with new generation challenges to service on the market. The aim is to monitor and provide automated support and recommendations to the start- ups to improve the business success rate in a personalized manner. Machine Learning (ML) can work on huge amounts of business-oriented data and can recover various kinds of patterns. The ML is a set of techniques for exploring essential patterns from raw data using mathematical algorithms [3]. The collection of algorithms is used to investigate and understand the different relationships among two or more business-centric attributes. Thus using these techniques we are enabled to classify, categorize, and/or make predictions using the collected or available data. These methods may involve different kinds of algorithms, based on classification, clustering, association rule mining, and others. Based on the use of the application of data patterns these methods or algorithms are applied to the data. In this section, we provide a brief overview of the proposed business intelligence tool.

II. LITERATURE REVIEW

The given section introduces the different techniques that are recently developed for predicting the startup success and preparing any framework that help to sustain and grow new business using machine learning techniques.

On account of organizations that total information about different firms, it has gotten conceivable to make and approve prescient models dependent on a remarkable measure of true models. K. Żbikowski et al [4] utilizes information from Crunchbase. The point is to make a prescient model dependent on ML for estimating an organization's prosperity. They planned analyses in a manner that forestall the spilling of any data at the definitive second. Creators analyzed Logistic Regression (LR), Support Vector Machine (SVM), and the Gradient Boosting (GB) classifier. The model arrived at promising outcomes as far as accuracy, review, and F1 scores (57%, 34%, and 43%). The best results were acquired with the GB classifier. They give data about the significance of highlights.

B. Sharchilev et al [5] consider the issue of foreseeing the accomplishment of new businesses at beginning phases. They figure the undertaking as anticipating whether an organization that has effectively gotten beginning subsidizing will draw in a further round. They examine the capability of electronic open hotspots for the startup achievement forecast and model utilizing a rich arrangement of signs. Advance organized information about the startup biological system with data from a business-and work arranged long range interpersonal communication and from the web. Utilizing these, they train a ML pipeline with numerous base models. They show that using organizations' notices on the Web yields a generous presentation. They likewise give an examination of the acquired model.

A few reasons are liable for the disappointment of a startup. A. Krishna et al [6] plan to make a prescient model for new businesses, in view of numerous things required at different stages. It is profoundly attractive to expand the achievement pace of new businesses. They propose a strategy to anticipate the result of new businesses dependent on factors like seed financing sum, time, Series of subsidizing. They have made a few models based on the data like Crunchbase, Tech Crunch, etc. Several data mining techniques were used on the pre- processed data along with optimizations and validations. They provide analysis using Random Forest (RF), ADTrees, and Bayesian Networks (BN). They evaluate the correctness of models based on the area under the ROC curve, precision, and recall.

H. Janáková et al [7] manages conditions for the arrangement of an innovation fire up. They sum up current and forthcoming conditions, and also. On genuine instances of AeroMobile and eSense are dealt with. The creator is looking at the advancement in SR since the time of the initial beginning up. They are preparing areas for new companies are appropriate. The improvement in the IT new businesses is centered rigorously around deals, while fire up in regions is confronting locally. New businesses with funding are intended for ensuing resale to financial backers. Estimation the achievement is a subject that has been gotten sure consideration. The goal is to examine and explain how to assess and reexamine estimation frameworks, utilizing materials and writing to research and quantify proficiency. They set and legitimize the propriety.

Utilizing a major informational collection of investment financing and related startup firms from Crunchbase, G. Ross et al [8] foster a ML model called CapitalVX to anticipate the results for new businesses, i.e., regardless of whether they will exit effectively through an IPO or procurement, fall flat, or stay private. Utilizing a huge list of capabilities, the exactness of forecasts on startup results and follow-on subsidizing is 80- 89%. They propose that VC/PE firms might have the option to profit with utilizing ML to screen speculations utilizing accessible data.

U. Kaiser et al [9] use textual and non-textual data from openly accessible files to anticipate the exhibition of new companies. They think about endurance, business development, return on resources, new patent, and endowment. They consider a base detail that incorporates authoritative document, area, possession, and industry. Add variable sets addressing firm names, business articulations, originators, and startup attributes. To estimate, we just need to incorporate a bunch of factors got from BPS messages. A precise gauge of business development needs a blend of BPS and organizer attributes. Every one of the estimates need to effectively realistic since the fundamental data is compulsory.

A critical fixing to a startup's prosperity is its capacity to raise subsidizing. Crowdfunding has another system for interfacing new companies with a large number of financial backers. Q. Zhang et al [10] play out a longitudinal information assortment and investigation of AngelList. Over a 7-multi month time frame, track organizations that are effectively raising money, and record their degree of social commitment. Through a progression of measures on friendly commitment, examination shows that dynamic commitment via online media is profoundly related to crowdfunding. At times, the commitment level is greatness higher for effective organizations. Further apply choice tree, SVM, KNN, and so forth to anticipate the capacity of an organization to effectively ascend to finance. Besides, notwithstanding the class irregularity, models can anticipate accomplishment with 84% precision.

As indicated by A. Prohorovs et al [11] just a little level of new companies draw in capital from funding financial backers. To decide the variables which think about the significance of drawing in speculations, the originators of 40 new companies were addressed. The scientists thought about authoritative and monetary variables' for two gatherings of business visionaries. The outcomes show certain contrasts between the perspectives of organizers and financial backers in regards to progress factors.

Investing in early-stage companies is hard when no data are available. Venture capitalists often rely on gut feeling to reach a decision. F. Corea et al [12] proposes a framework to help investors in selecting companies with a higher probability of success. They built research and augmented it with analysis on more than 600,000 companies. The framework is a smart checklist of 21 features that may help investors.

The tools available are not enough to reduce risk and managing uncertainty. ML approaches can bridge this gap. These approaches are possible because of data from thousands of companies through Crunchbase. Previous efforts have focused on predicting two classes, i.e., being acquired or offering shares. J. Arroyo et al [13] will try to predict possible outcomes including subsequent funding or the closure. That approach would provide VC investors to set up a portfolio with lower risk and higher returns. They will analyze the performance of several ML methods, in a dataset of over 120,000 companies and tries to predict their progress.

Interactions on social media can reveal remarkably predictions about future events. T. Antretter et al [14] show that online legitimacy as a measure of social appreciation based on Twitter content to predict new venture survival. They analyze more than 187,000 tweets from 253 ventures' accounts using ML approaches. The findings suggest that they can correctly discriminate failed ventures up to 76%. They contribute to the discussion on the importance of ML in entrepreneurship research.

D. McKenzie et al [15] analyze the total and relative exhibition of three ways to deal with foreseeing results for strategy contest: Scores from judges, straightforward impromptu models utilized, and ML draws near. They find that I) strategy scores are uncorrelated with endurance, work, deals, or benefits; ii) hardly any critical attributes of business visionaries like sex, age, capacity, and business area; iii) present day ML techniques don't offer enhancements; iv) the in general prescient force of approaches is exceptionally low.

M. Guerzoni et al [16] shows how information science can add to further developing examination in financial aspects. As a testbed, ML permits making another proportion of development keeping Italian Law pointed toward boosting new firms. They receive to investigate the effect of imaginativeness on a huge populace. To begin with, they train seven regulated learning calculations to perceive creative firms on 2013 firmographics information. Second, apply the last on the 2008 dataset and foresee which firms would have been marked as creative. At long last, embrace this new pointer as the regressor in an endurance model to disclose firms' capacity to remain.

Animate and work on the pace of accomplishment of R&D coordinated effort by SMEs, S. P. Jun et al [17] fostered a technique for suggesting kinds of outside joint effort associations that are ideal accomplices. They started by analyzing the current information to group the sorts of R&D accomplices drew in with SMEs. Then, applied ML and discriminant examination for suggesting firms that will accomplish high fulfillment with four kinds of R&D accomplices. Finally, they utilized new information that had not been remembered for the model turn of events, to perform assessments. As result, the suggestion model shows exceptional precision 91%. By applying the model, firms will actually want to choose R&D accomplice types all the more effectively and improve making progress.

J. C. Kaminski et al [18] presents a neural organization and normal language preparing (NLP) way to deal with foresee the result of crowdfunding startup utilizing text, discourse, and video metadata in 20,188 crowdfunding efforts. Semantic styles in crowdfunding efforts expect to trigger fervor or are focused on comprehensiveness are better indicators of mission achievement. Higher vulnerability about the condition of item improvement may decrease assessments of new items and diminish buying aims. The discoveries underscore that positive mental language is notable in conditions where the goal is scant and venture inclinations are taste-based. Utilizing excited language or showing the item in real life may catch a person's consideration.

The point of J. R. Saura et al [19] is to distinguish the elements on Twitter for the production of fruitful new companies, and for maintainable new businesses. They proposed to recognize the key components. Initial, a Latent Dirichlet Allocation (LDA) was utilized, which decides the information base theme. Also, a Sentiment Analysis was performed with SVM to separate the startup points into negative, positive, and nonpartisan. Thirdly, a Textual Analysis was conveyed with Text Mining strategies. They identified that the points with good affections for the startup achievement are an innovation based startup, the disposition of the originators, and the procedure. The negative subjects are the structures and programming dialects, sort of work, and holy messengers' prerequisites. The impartial subjects are the improvement of the field-tested strategy, sort of startup, and the hatcheries and geo-area. The constraints are the quantity of tweets tests and the restricted time.

III. PRELIMINARIES

The business location is an important component for entrepreneurs. Business in optimal location; not only the satisfaction level of the customers but also it maximizes the profit. T. Bilen et al [20] propose an application that uses ML techniques to estimate the location. The system collects features for a specific business and learns for future data. It estimates features and suggests clusters of districts that have optimal locations. The system is evaluated on a use case that estimates the best possible locations of a restaurant. The first phase of the decision process is estimating mentioned features. They determine an optimal regression model according to each feature. The second phase clusters districts according to these estimated features by using the hierarchical tree.

It is interested to see that writing will in general zero in on fruitful new companies and on quantitative examinations for determinants of progress. M. Cantamessa et al [21] means to fill this hole and contribute by giving a repeatable and adaptable technique applied to data sets of unstructured archives. Further related commitment is the investigation completed to an enormous information base. Expressive insights show how the absence of an organized Business Development system arises as a critical determinant of startup disappointment.

This wasteful nature of organizations is influencing the development of their economy. I. Afolabi et al [22] give a business achievement analysis framework. The point is to presents a plan for the determination, forecast, and proposal. They foster the forecast depends on connection examination for the information and the mix of Naïve Bayes and J48 arrangement. Heuristics for the finding were ordered from the audit of existing counseling frameworks, master frameworks, and human specialists. The framework will work on the pace of business achievement and give a stage to enterprising improvement.

However, enterprises show different maturity levels in implementing ML techniques. M. Bauer et al [23] review the state of adoption of ML in enterprises. They find that ML technologies are being adopted in enterprises, but SMEs are struggling in comparison to larger enterprises. To identify enablers and success factors authors conduct a qualitative study. The results show that SMEs fail to apply ML technologies due to insufficient ML knowledge.

Location and forecast of organization defaults and chapter 11, critical exertion has been committed. This issue becomes significant when monetary chiefs are furnished with expectations, in view of the yield of forecast models. G. Perboli et al [24] center around mid-and long haul forecasts focusing on SMEs. The key commitment is an improvement

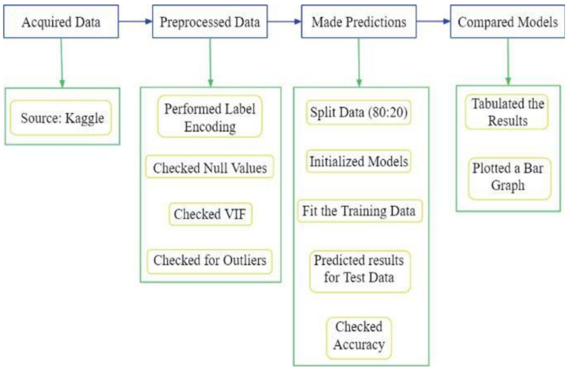
Considering the new COVID-19 pandemic, the creators show how the strategy can be utilized as an instrument for enormous scope strategy making.

IV. SYSTEM MODEL

1. Data Collection: Gather comprehensive data related to start- up finances, market conditions, industry trends, and any other relevant variables that could affect profits.
2. Data Preprocessing: Clean and preprocess the

data to handle missing values, outliers, and ensure it is in a format suitable for machine learning algorithms.

3. Feature Engineering: Identify key features that could significantly impact profit predictions and create new features if needed to enhance the model's performance.
4. Model Selection: Explore various machine learning algorithms such as linear regression, decision trees, random forests, or neural networks to determine the best model for your prediction system.
5. Model Training: Split your data into training and testing sets, train your selected model on the training data, and evaluate its performance using the testing data.
6. Model Evaluation and Fine-Tuning: Assess the model's accuracy, precision, and recall to fine-tune its parameters and improve its predictive capabilities.
7. Deployment: Once you have a well-performing model, deploy it into a production environment where it can make real-time profit predictions for start-ups.



V. METHODLOGY

1. Problem Definition: Clearly define the problem you aim to solve with the profit prediction system. Determine what factors influence a start-up's profitability and how machine intelligence can help predict future profits.
2. Data Collection: Gather relevant data sources such as financial records, customer data, market trends, and any other information that can impact profits.
3. Data Preprocessing: Clean the data by handling missing values, outliers, and formatting it appropriately for analysis.
4. Feature Engineering: Identify important features that can influence profit predictions and create new features if needed to enhance the model's accuracy.
5. Model Selection: Choose a suitable machine learning algorithm such as linear regression, decision trees, random forests, or neural networks based on the nature of the data and the problem at hand.
6. Model Training: Split the data into training and testing sets, train the selected model on the training data, and tune its parameters to optimize performance.
7. Model Evaluation: Evaluate the model's performance using metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), or Mean Absolute Error (MAE) to assess its accuracy in predicting profits.
8. Deployment: Deploy the trained model into a production environment where it can make real-time profit predictions for start-ups.
9. Monitoring and Maintenance: Continuously monitor the model's performance, retrain it periodically with new data, and update it as needed to ensure its predictions remain accurate over time.

VI. IMPLEMENTATION

1 Data Collection and Preprocessing

The implementation process begins with the collection of relevant startup data including investment capital, industry type, location, team size, operational costs, revenue, and other business metrics. Government schemes data such as eligibility criteria, benefits, and categories were also collected from public government portals and startup India websites.

Data preprocessing is performed to clean and transform raw data into a usable format. Missing values are handled, categorical data is encoded, and normalization is applied to ensure uniform data scaling. Feature selection techniques such as correlation matrix and mutual information are used to identify the most significant predictors for the profit forecast model.

2 Machine Learning Model Development

Multiple machine learning algorithms are tested and compared to find the most accurate model for profit prediction. Models such as Linear Regression, Random Forest Regressor, Support Vector Regressor (SVR), and XGBoost are evaluated using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score. After cross-validation and hyperparameter tuning, the best-performing model is selected and integrated into the backend of the application.

For the government scheme recommendation engine, a content-based filtering approach is implemented. The system matches startup features like industry, stage, and location with government schemes that have similar eligibility criteria. This ensures personalized and relevant suggestions for startup founders.

3 System Architecture and Backend Integration

The system follows a modular architecture that separates the frontend, backend, and ML model components. The backend is built using Python and Flask, which handles data input, model execution, and result retrieval. The ML model is deployed using joblib or pickle for model persistence and quick prediction serving. A lightweight SQLite or MySQL database is used for storing user details, startup inputs, prediction logs, and matched schemes.

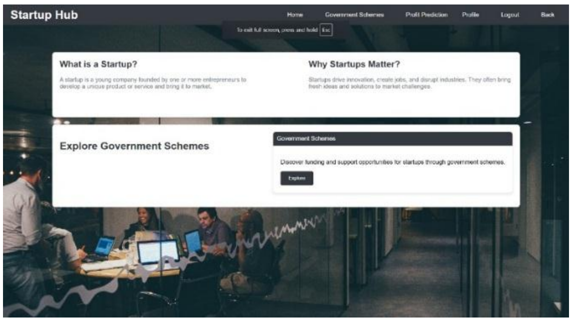
4 Frontend Development

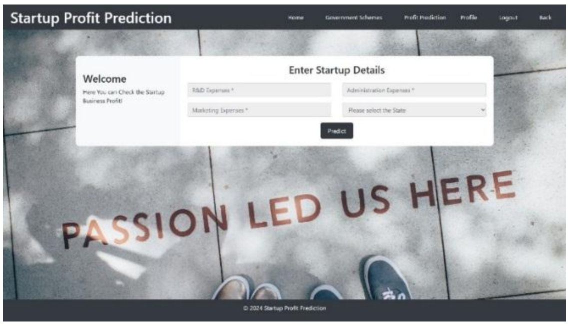
A user-friendly web interface is created using HTML, CSS, JavaScript, and Bootstrap to allow startups to input their details and view prediction results. The dashboard includes sections for input forms, prediction outputs (profit graph and value), and scheme recommendations. Visualizations such as profit trend graphs and pie charts are implemented using Chart.js or Plotly to enhance user understanding.

VII. SECURITY ANALYSIS

1. Data Security: Implement robust data encryption techniques to safeguard sensitive information such as financial data and customer details. Utilize secure data storage practices and access controls to prevent unauthorized access.
2. Model Security: Protect the machine learning models from adversarial attacks by applying techniques like model encryption, input sanitization, and monitoring for unusual behavior that could indicate a security breach.
3. System Architecture: Design a secure system architecture that segregates components, implements secure communication protocols, and restricts access based on user roles and permissions.
4. Regular Audits: Conduct regular security audits and vulnerability assessments to identify and address potential security weaknesses in the system.
5. User Authentication and Authorization**: Implement robust user authentication mechanisms such as multi-factor authentication and role-based access control to ensure that only authorized users can interact with the system.
6. Monitoring and Logging: Set up monitoring tools to track system activities, detect anomalies, and generate logs for auditing purposes. Monitor system performance and security metrics to proactively identify and address security issues.
7. Incident Response Plan: Develop a comprehensive incident response plan outlining procedures to follow in the event of a security breach. Ensure all team members are trained on how to respond to security incidents effectively.
8. Compliance: Ensure that the profit prediction system complies with relevant data protection regulations such as GDPR, HIPAA, or industry-specific standards to maintain data privacy and security.

VIII. RESULTS





IX. PERFORMANCE ANALYSIS

Data pre-processing can often have a critical impact on general performance of a supervised machine learning task. The process will follow general changes (as transversal to all thirteen tables in-use) and changes made to the organizations table as it is where all relevant information converges, ultimately becoming the training dataset of the task at hands. Due to the nature of the data and problem the priority is understanding its interdependence and not minimizing correlations. The data pre-processing consists in a 3-step process:

- Data cleaning, where the author aims to remove all redundant and irrelevant information from the database as well as duplicates, missing values and outliers. The explanation of this process is divided between specific changes in the 'Organizations' table and general changes made transversely in all tables;
- Data selection, where the context of the study (i.e., social- demographic criteria) is defined to filter which data will be taken into the final dataset and
- Data transformation, consisting on the process of creating new variables or aggregating data from different tables into organization's table.

CONCLUSIONS

The machine learning techniques are being used for the analysis of various business activities and other relevant purposes. That improves the working of business, process large amount of data, reduces human efforts and errors, and improve sustainability and growth. In this context, new business sustainability is a great challenge worldwide. This topic is recently getting much attention because of new global business challenges and issues i.e. covid-19. In order to minimize the risk and understanding the key factors of a successful startup, in this paper we are proposed to review the recent research work and contributions. Understanding and predicting the possibility of a startup's success can depend on a number of influencing features. Among them seed funding, risk assessment, planning and the viewpoint of investors and founders are essential. However, the startup prediction can minimize the investor's risk and maximize the possible future profits. On the other hand, predictive modeling using ML techniques for startup success not only useful for investors it is also helpful to understand the gap of the startup as feedback for improvement. Using the different features and success indicators we can not only predict a startup's success or failure, but the startup also gets actionable insights for their own improvements. In addition to that for identifying the success or failure, a different source of data will be used. That can depend on the type of startup project and their coverage. Finally, we can see there are a number of supervised and unsupervised learning techniques are used for designing prediction as well recommendation models. Among most of the techniques are influenced by regression analysis and classical machine learning algorithms. In some of the cases, supervised learning and NLP-based techniques are also contributing to identifying the success and failure of an online startup business. Finally, by influencing the identified facts and methodologies we conclude some essential facts that are useful for our future research work are highlighted in the next sections. Additionally, by concluding them we also provide the future road map of the proposed research work in order to predict and recommend the essential features which improve the sustainability of new startup projects.

REFERENCES

[1] https://www.startupindia.gov.in/

[2] https://ficci.in/

[3] Pujari, Arun K., "Data Mining Techniques", Universities press, 2001.

[4] K. Żbikowski, P. Antosiuk, "A machine learning, bias-free approach for predicting business success using Crunch base data", Information Processing and Management 58 (2021) 102555

[5] B. Sharchilev, M. Roizner, A. Rumyantsev, D. Ozornin, P. Serdyukov, M. de Rijke, "Web-based Startup Success Prediction", CIKM 2018, October 22–26, Lingotto, Turin, Italy © Copyright held by the owner/author(s). ACM ISBN 123- 4567-24-567/08/06

[6] A. Krishna, A. Agrawal, A. Choudhary, "Predicting the Outcome of Startups: Less Failure, More Success", IEEE 16th International Conference on Data Mining Workshops, 2375- 9259/16© 2016 IEEE

[7] H. Janáková, "The Success Prediction of the Technological Start–up Projects in Slovak Conditions", Procedia Economics and Finance 34 (2015) 73 – 80

[8] G. Ross, S. Das, D. Sciro, H. Raza, "CapitalVX: A machine learning model for startup selection and exit prediction", The Journal of Finance and Data Science 7 (2021) 94-114

[9] U. Kaiser, J. M. Kuhn, "The value of publicly available, textual and non-textual information for startup performance prediction", Journal of Business Venturing Insights 14 (2020) e00179

[10] Q. Zhang, T. Ye, M. Essaidi, S. Agarwal, V. Liu, B. T. Loo, "Predicting Startup Crowd-funding Success through Longitudinal Social Engagement Analysis", CIKM'17, November 6–10, 2017, Singapore, ACM ISBN 978-1-4503- 4918-5/17/11

[11] A. Prohorovs, J. Bistrova, D. Ten, "Startup Success Factors in the Capital Attraction Stage: Founders' Perspective", Journal of East-West Business, DOI: 10.1080/10669868.2018.1503211

[12] F. Corea, G. Bertinetti, E. M. Cervellati, "Hacking the venture industry: An Early-stage Startups Investment framework for data-driven investors", Machine Learning with Applications 5 (2021) 100062

[13] J. Arroyo, F. Corea, G. J. Diaz, J. A. Recio-Garica, "Assessment of Machine Learning Performance for Decision Support in Venture Capital Investments", Volume 7, 2019, IEEE

[14] T. Antretter, I. Blohm, D. Grichnik, J. Wincent, "Predicting new venture survival: A Twitter-based machine learning approach to measuring online legitimacy", Journal of Business Venturing Insights 11 (2019) e00109

[15] D. McKenzie, D. Sansone, "Predicting entrepreneurial success is hard: Evidence from a business plan competition in Nigeria", Journal of Development Economics 141 (2019) 102369

[16] M. Guerzoni, C. R. Nava, M. Nuccio, "Start-ups survival through a crisis Combining machine learning with econometrics to measure innovation", Economics of Innovation and New Technology, DOI: 10.1080/10438599.2020.1769810.

[17] S. P. Jun, H. S. Yoo, J. Hwang, "A hybrid recommendation model for successful R&D collaboration: Mixing machine learning and discriminant analysis", Technological Forecasting & Social Change 170 (2021) 120871

[18] J. C. Kaminski, C. Hopp, "Predicting outcomes in crowdfunding campaigns with textual, visual, and linguistic signals", Small Bus Econ (2020) 55:627–649

[19] J. R. Saura, P. P. Sanchez, A. Grilo, "Detecting Indicators for Startup Business Success: Sentiment Analysis Using Text Data Mining", Sustainability 2019, 11, 917; doi:10.3390/su11030917

[20] T. Bilen, M. E. Ozcevik, Y. Yaslan, S. F. Oktug, "A Smart City Application: Business Location Estimator using Machine Learning Techniques", 978-1-5386-6614-2/18/$31.00 ©2018 IEEE, DOI 10.1109/HPCC/SmartCity/DSS.2018.00219

[21] M. Cantamessa, V. Gatteschi, G. Perboli, M. Rosano, "Startups' Roads to Failure", Sustainability 2018, 10, 2346; doi:10.3390/su10072346

[22] I. Afolabi, T. C. Ifunaya, F. G. Ojo, C. Moses, "A Model for Business Success Prediction using Machine Learning Algorithms", IOP Conf. Series: Journal of Physics: Conf. Series 1299 (2019) 012050 doi:10.1088/1742-6596/1299/1/012050

[23] M. Bauer, C. van Dinther, D. Kiefer, "Machine Learning in SME: An Empirical Study on Enablers and Success Factors", AMCIS 2020 Proceedings. 3