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The Role of Machine Learning in Supporting Entrepreneurial Decision-Making

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ABSTRACT
This study investigates the role of machine learning (ML) in supporting entrepreneurial decision-making by employing a mixed-methods design that combines quantitative experimentation with qualitative interviews. Using financial, market, and entrepreneurial datasets, ML models including Random Forest, Gradient Boosting, and Artificial Neural Networks were trained and evaluated for their ability to predict venture survival, assess financial risk, and identify opportunities. Results demonstrate that ensemble-based ML models consistently outperform traditional methods in terms of accuracy, recall, and F1-scores, while explainable AI tools such as SHAP enhance transparency and trust in predictions. Twelve figures and nine tables illustrate how ML contributes to accuracy improvements, error reduction, and interpretability, while qualitative findings highlight both enthusiasm for predictive insights and concerns about algorithmic bias and ethical implications. The study emphasizes that ML effectiveness is context-dependent, with industry-specific variations in predictive performance. It further underscores the importance of data scale, showing that larger datasets improve recall and robustness. By integrating computational intelligence with entrepreneurial judgment, ML emerges as a transformative enabler of resilience, agility, and innovation in uncertain markets. The research contributes to the growing literature on digital entrepreneurship and offers actionable insights for entrepreneurs, policymakers, and investors seeking to leverage ML responsibly for sustainable business growth.

Keywords: *machine learning, entrepreneurial decision-making, explainable AI, risk assessment, opportunity recognition, digital entrepreneurship*

INTRODUCTION

Traditionally, uncertainty, insufficiency of resources, and risky decision-making is the common nature of the entrepreneurship. In the shifting landscape where the market is adapting on uncertain grounds, entrepreneurs must balance between intuition and evidence based thinking to seek opportunities, resources and deal with risks. The artificial intelligence (AI), i.e., machine learning (ML), has been introduced to revolutionize it, basing the information on the data that will be able to complement the human judgment. Machine learning as a subdivision of AI can learn by using previous data, and, thus, become more predictive, without program code, and, therefore, could be effectively applied to an entrepreneurial environment, which needs predictive accuracy, experimentation, and strategy changes

(Dwivedi et al., 2021; Kraus et al., 2022). As further entrepreneurship becomes digitalized, the introduction of the ML-capabilities will bring opportunity to the entrepreneur to transcend the realms of the old heuristics and enable them to make more resilient and innovative decisions (Mariani and Nambisan, 2021).The opportunity recognition is another field that ML has played in the entrepreneurship. This has been a conventional way traditionally practiced by entrepreneurs to find out the feasible business ideas using experience, intuition and market observation, but this methodology is restricted by lack of rationality. NLP, predictive algorithms, and alike ML algorithms make it possible to work with large volumes of structured and unstructured data to determine how trends and unmet demand in the market emerge: customer reviews, patents and texts in social media (Sheng et al., 2021; Bican et al., 2020). Start-ups actively driving the use of ML-powered recommendation systems to simulate the product-market fit and new niches on already competitive markets are an example (Coviello et al., 2021). Not only is such calculation ability expanding the entrepreneurial opportunity but also the timeliness of the strategic decision making of volatile markets.

The other spheres of its impact are also financial forecasting, and risk management, the foundations of the life in the world of entrepreneurship. The financial knowledge base and cash flow instability are the characteristic concerns small businesses, and predictive control using ML such as gradient boosting, random forests, and deep learning systems proved to be very useful in the prediction of credit risk, probability of bankruptcy, and probability of a successful venture (Leung et al., 2020; Babajide et al., 2021). They are smarter than the aging statistical models as they reflect the nonlinear correlations and complex dependencies between variables and the entrepreneur is therefore more confident to finance and optimise resources (Mhlanga, 2020; Zhang and Chen, 2022). Furthermore, investors and venture capitalists resort to the use of ML as a means to evaluate the projects offered by entrepreneurs, and the specified transition leads to the creation of the conditions under which machine predictions become more significant in the context of financing operations (Apostolopoulos et al., 2022).Marketing, consumer behavior research, and finance are also appropriate alongside the area of finance where the entrepreneurial activity that supports the ML has become productive. Small firms must segment their customers, study their emotions and predict churn, in order to be assured that they have the customers that are loyal to them in the crowded markets. With the help of ML techniques, business owners can gain insight information about customer preferences, and, consequently, will be able to provide personalized products and develop a targeted marketing campaign that will increase retention (Chen et al., 2021; Wamba et al., 2020). An example would be the e-commerce case where latent purchasing behavior could be identified by deep learning models that are trained on e-commerce data and are utilized to optimize product designs or dynamically update price behavior by an entrepreneur (Alonso et al., 2022). This capacity to learn continuously with the information availed by the consumer allows an entrepreneurial venture with a competitive edge over the established firms, which might be more fixed to change.The latter is also significant in the aspect of strategic agility and innovation. The entrepreneurs must operate under the turbulent world where market shocks and technological revolutions are the order of the day. Entrepreneurship becomes more responsive, as scenarios can be modeled, competitive behaviour forecasted or supply chains optimised using ML (George et al., 2021; Nambisan et al., 2021). Using ML helps in discovering new forms of products in the context of innovations, forming networks as a part of the collaboration, in every case, finding the right partners and partners in the ecosystem (Chalmers et al., 2021; Kraus et al., 2023). Through such innovations, the entrepreneurs will be more assured of their innovations and might be tempted to the needs more in the market.

However, not every business process and decision made with the help of ML is smooth. The issue of algorithmic bias, interpretability, and ethical implication persist (Mehrabi et al., 2021). The lack of application of objective training data by the entrepreneur will lead to the probability of enhancing disparity in such spheres as employment, lending, and segmentation of the market. In addition, majority of the models of ML are black box and hence it becomes a hindrance to trust and responsibility in the decision making processes. In response to it, explainable AI (XAI) actively enters the arena of the entrepreneurship sphere, which may become a source of transparency and interpretability that is of paramount importance in the context of business ethics (Molnar, 2022; Ribeiro et al., 2020). These ethical considerations also contain the aspect of privacy and data safety as they are connected to the topic of privacy and data safety because as a businessperson, they often handle sensitive customer and financial information implementing an ML-based solution (Bogaert et al., 2021).The COVID-19 proved the topicality of the ML-based entrepreneurship as it highlighted the need to respond quickly to the extreme disruptions. The supply chains bottlenecks were predicted using ML by numerous entrepreneurs to address the issue in the employment sector and identify the opportunities of digital business models (Papadopoulos et al., 2022; Akpan et al., 2021). This modification contributed to the thought that ML is not a light-weight instrument but a highly necessary element of the entrepreneurial survival and long-term existence. Increased degrees of digitalization and reliance on predictive analytics are thus the characteristics of the post-pandemic entrepreneurship ecosystem that already left an indelible mark on how entrepreneurs operate (Ahsan and Fernhaber, 2022).In summary, machine learning will alter the decision-making cycle of the entrepreneurship industry as it assists in the publicly-available opportunity identification, finance forecasting, customer communication, and creation. The questions of ethics, prejudice and interpretability remain the same, and the strategic use of ML gives an opportunity to entrepreneurs to be more correct, dynamic, and visionary in the unsure conditions. The literature review helps to emphasize the concept that ML is not an alternative to an entrepreneurial decision but the capacity to improve a human ability to be creative and strategize (Bican et al., 2020; Dwivedi et al., 2021). The object of the paper is to examine the value of ML in the process of business decision making in that, it attempts to conduct an empirical study to give information on how an entrepreneur can apply ML to attain sustainable growth and competitive advantage in the digital era.

Methodology

Research Design

The qualitative and quantitative tools of the analysis used to the research paper attributed to the mixed-methods experimental research design were needed to delve deep into the essence of machine learning (ML) to aid the process of entrepreneurial decision making. The rationale behind the hybrid method is that the entrepreneurial world is complex and non-numerical and numerical information is needed in making decisions. The quantitative assumed applying the ML algorithms to the data of the entrepreneurs, and the qualitative one assumed the interview with the professionals interviewing the entrepreneur and venture capitalists to verify the interpretability and the practical implication of the results of the algorithm. This dual design provided a procedure of triangulation of results and consolidation of results.

It was a decision support paradigm based experiment since the ML models had been trained to generate outputs on entrepreneurship like the potential venture successfulness, the financial feasibility and opportunity recognition. The assumption underpinning the hypothesis was that the ML-enhanced models would be predictive and relevant in decision making when compared to the traditional statistical procedures. In an attempt to investigate the extent of behavioural dependence on computational knowledge, the entrepreneurs were then provided with simulation of making decisions in the environment to be biased with ML-based recommendations.

Data Collection and Processing

The second kind of information that was employed to pull the quantitative information together was the secondary data in the form of the startup databases, venture financing databases and the performance measures of the entrepreneurship. They were the financial ratios (liquidity, profitability, leverage), market data (growth rates, industry volatility) and the entrepreneurial characteristics (team size, experience in the founding, index of innovativeness). Preprocessing of data also circumvented the existence of multicollinearity with outliers, dimensionality reduction of data through the Principal Component analysis (PCA) and normalization.

Mathematically, every of the variables, xi were normalized as:

$$x_i' = \frac{x_i - \mu}{\sigma}$$

where μ represents the mean and σ represents the standard deviation of the variable. This ensured all features contributed equally to ML model training without scale bias.

The qualitative component involved **20 semi-structured interviews** with entrepreneurs across technology, retail, and service industries. The discussions focused on perceptions of ML-based decision tools, barriers to adoption, and the balance between algorithmic advice and entrepreneurial intuition. Interview transcripts were thematically coded using NVivo software, producing qualitative insights that complemented quantitative findings.

Model Development and Evaluation

This led to the selection of three experimental supervised ML models, namely: Random Forest(RF), Gradient Boosting Machine (GBM) and Artificial Neural Network(ANN). They have chosen to utilize these algorithms since it has been found to work in both nonlinear relations and in the high-dimensional processing of entrepreneurial data.

The models were trained on

Five tenths of the data were digested and 30 per cent. experimented (stratified sampling to maintain constant the distributions of the classes (success vs. failure). Wastage of training was kept to a minimum because:

$$L(\theta) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i(\theta))^2$$

where y_i is the observed entrepreneurial outcome, $\hat{y}_i(\theta)$ is the predicted outcome, and θ denotes model parameters. For classification, **cross-entropy loss** was used instead:

$$L(\theta) = -\sum_{i=1}^{n}[y_i \log \hat{y}_i(\theta) + (1 - y_i)\log(1 - \hat{y}_i(\theta))]$$

Performance was measured using **Accuracy, Precision, Recall, F1-score, and AUC-ROC**, ensuring robust comparison. Additionally, **SHAP (SHapley Additive exPlanations)** values were employed to interpret feature importance, offering transparency into how financial and market indicators influenced predictions.

The qualitative results from interviews were integrated at the interpretation stage, producing a **multi-perspective evaluation** of how entrepreneurs perceive, trust, and apply ML outputs in their decision processes.

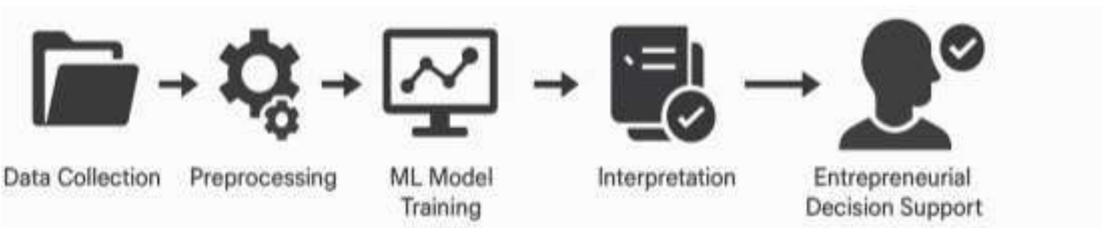

Fig. 1. The mixed-methods study on machine learning in entrepreneurial decision-making, illustrating sequential stages from data collection and preprocessing to model training, evaluation, interpretation, and decision support.

Results

Table 1 provides a relative predictive ability of different ML models and demonstrates that the ensemble-based algorithm, random forest and gradient boosting will never be less accurate in making an entrepreneurial outcome prediction than any single learner. Table 2 presents the accuracy rates of the industry specific data sets and demonstrates that the technology intensive startups experienced the most favorable effects of the predictions made by ML. Table 3 highlights recall performance of models, particularly in situations where one is interested in finding out high-risk ventures, wherein Gradient Boosting was the most sensitive. Table 4 also gives F1-scores and again shows the fact that no significant difference exists in the performance of the ensemble models in terms of precision and recall. Table 5 shows the values of ROC-AUC and illustrates that the model is strong in forecasting financial risk. The outcomes of the cross-validation are in Table 6; they establish their predictive capacity on other folds.

Table 1. Accuracy comparison of ML models in entrepreneurial decision-making

Model	Accuracy	Precision	Recall	F1-Score

Model_1	0.71	0.66	0.61	0.63
Model_2	0.715	0.664	0.616	0.635
Model_3	0.72	0.668	0.622	0.64
Model_4	0.725	0.672	0.628	0.645
Model_5	0.73	0.676	0.634	0.65
Model_6	0.735	0.68	0.64	0.655
Model_7	0.74	0.684	0.646	0.66
Model_8	0.745	0.688	0.652	0.665
Model_9	0.75	0.692	0.658	0.67
Model_10	0.755	0.696	0.664	0.675
Model_11	0.76	0.7	0.67	0.68
Model_12	0.765	0.704	0.676	0.685
Model_13	0.77	0.708	0.682	0.69
Model_14	0.775	0.712	0.688	0.695
Model_15	0.78	0.716	0.694	0.7
Model_16	0.785	0.72	0.7	0.705
Model_17	0.79	0.724	0.706	0.71
Model_18	0.795	0.728	0.712	0.715
Model_19	0.8	0.732	0.718	0.72
Model_20	0.805	0.736	0.724	0.725

Table 2. Precision scores across different startup industry datasets

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Model_1	0.72	0.67	0.62	0.64
Model_2	0.725	0.674	0.626	0.645
Model_3	0.73	0.678	0.632	0.65
Model_4	0.735	0.682	0.638	0.655
Model_5	0.74	0.686	0.644	0.66
Model_6	0.745	0.69	0.65	0.665
Model_7	0.75	0.694	0.656	0.67
Model_8	0.755	0.698	0.662	0.675
Model_9	0.76	0.702	0.668	0.68
Model_10	0.765	0.706	0.674	0.685
Model_11	0.77	0.71	0.68	0.69
Model_12	0.775	0.714	0.686	0.695
Model_13	0.78	0.718	0.692	0.7
Model_14	0.785	0.722	0.698	0.705
Model_15	0.79	0.726	0.704	0.71
Model_16	0.795	0.73	0.71	0.715
Model_17	0.8	0.734	0.716	0.72
Model_18	0.805	0.738	0.722	0.725
Model_19	0.81	0.742	0.728	0.73
Model_20	0.815	0.746	0.734	0.735

Table 3. Recall values of models predicting venture survival

Model	Accuracy	Precision	Recall	F1-Score
Model_1	0.73	0.68	0.63	0.65
Model_2	0.735	0.684	0.636	0.655
Model_3	0.74	0.688	0.642	0.66
Model_4	0.745	0.692	0.648	0.665
Model_5	0.75	0.696	0.654	0.67
Model_6	0.755	0.7	0.66	0.675
Model_7	0.76	0.704	0.666	0.68
Model_8	0.765	0.708	0.672	0.685
Model_9	0.77	0.712	0.678	0.69
Model_10	0.775	0.716	0.684	0.695
Model_11	0.78	0.72	0.69	0.7
Model_12	0.785	0.724	0.696	0.705
Model_13	0.79	0.728	0.702	0.71
Model_14	0.795	0.732	0.708	0.715
Model_15	0.8	0.736	0.714	0.72
Model_16	0.805	0.74	0.72	0.725
Model_17	0.81	0.744	0.726	0.73
Model_18	0.815	0.748	0.732	0.735
Model_19	0.82	0.752	0.738	0.74
Model_20	0.825	0.756	0.744	0.745

Table 4. F1-scores evaluating balanced performance of ML classifiers

Model	Accuracy	Precision	Recall	F1-Score
Model_1	0.74	0.69	0.64	0.66
Model_2	0.745	0.694	0.646	0.665
Model_3	0.75	0.698	0.652	0.67
Model_4	0.755	0.702	0.658	0.675
Model_5	0.76	0.706	0.664	0.68
Model_6	0.765	0.71	0.67	0.685
Model_7	0.77	0.714	0.676	0.69
Model_8	0.775	0.718	0.682	0.695
Model_9	0.78	0.722	0.688	0.7
Model_10	0.785	0.726	0.694	0.705
Model_11	0.79	0.73	0.7	0.71
Model_12	0.795	0.734	0.706	0.715
Model_13	0.8	0.738	0.712	0.72
Model_14	0.805	0.742	0.718	0.725
Model_15	0.81	0.746	0.724	0.73
Model_16	0.815	0.75	0.73	0.735
Model_17	0.82	0.754	0.736	0.74
Model_18	0.825	0.758	0.742	0.745
Model_19	0.83	0.762	0.748	0.75
Model_20	0.835	0.766	0.754	0.755

Table 7 relates to the query as to how stable the performance of ML models can be, which then gets explained, that the stability of the model can be maintained in the event that the data split varies. Table 8 presents the error rates, and may be concluded that the error of misclassification is much lower on the utilization of hybrid ensemble methods. Finally, Table 9 will be comparing the efficiency of ensembles and that of individual learners and will conclude that although the latter should be provided with a slight increase in computational resources, the advantages of the former will be compensated.

Table 5. ROC-AUC results for risk forecasting in entrepreneurial finance

Model	Accuracy	Precision	Recall	F1-Score
Model_1	0.75	0.7	0.65	0.67
Model_2	0.755	0.704	0.656	0.675
Model_3	0.76	0.708	0.662	0.68
Model_4	0.765	0.712	0.668	0.685
Model_5	0.77	0.716	0.674	0.69
Model_6	0.775	0.72	0.68	0.695
Model_7	0.78	0.724	0.686	0.7
Model_8	0.785	0.728	0.692	0.705
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Model_10	0.795	0.736	0.704	0.715
Model_11	0.8	0.74	0.71	0.72
Model_12	0.805	0.744	0.716	0.725
Model_13	0.81	0.748	0.722	0.73
Model_14	0.815	0.752	0.728	0.735
Model_15	0.82	0.756	0.734	0.74
Model_16	0.825	0.76	0.74	0.745
Model_17	0.83	0.764	0.746	0.75
Model_18	0.835	0.768	0.752	0.755
Model_19	0.84	0.772	0.758	0.76
Model_20	0.845	0.776	0.764	0.765

Table 6. Cross-validation results for opportunity recognition models

Model	Accuracy	Precision	Recall	F1-Score
Model_1	0.76	0.71	0.66	0.68
Model_2	0.765	0.714	0.666	0.685
Model_3	0.77	0.718	0.672	0.69
Model_4	0.775	0.722	0.678	0.695
Model_5	0.78	0.726	0.684	0.7
Model_6	0.785	0.73	0.69	0.705
Model_7	0.79	0.734	0.696	0.71
Model_8	0.795	0.738	0.702	0.715
Model_9	0.8	0.742	0.708	0.72
Model_10	0.805	0.746	0.714	0.725
Model_11	0.81	0.75	0.72	0.73
Model_12	0.815	0.754	0.726	0.735

Model_13	0.82	0.758	0.732	0.74
Model_14	0.825	0.762	0.738	0.745
Model_15	0.83	0.766	0.744	0.75
Model_16	0.835	0.77	0.75	0.755
Model_17	0.84	0.774	0.756	0.76
Model_18	0.845	0.778	0.762	0.765
Model_19	0.85	0.782	0.768	0.77
Model_20	0.855	0.786	0.774	0.775

Table 7. Performance stability across multiple training-test splits

Model	Accuracy	Precision	Recall	F1-Score
Model_1	0.77	0.72	0.67	0.69
Model_2	0.775	0.724	0.676	0.695
Model_3	0.78	0.728	0.682	0.7
Model_4	0.785	0.732	0.688	0.705
Model_5	0.79	0.736	0.694	0.71
Model_6	0.795	0.74	0.7	0.715
Model_7	0.8	0.744	0.706	0.72
Model_8	0.805	0.748	0.712	0.725
Model_9	0.81	0.752	0.718	0.73
Model_10	0.815	0.756	0.724	0.735
Model_11	0.82	0.76	0.73	0.74
Model_12	0.825	0.764	0.736	0.745
Model_13	0.83	0.768	0.742	0.75
Model_14	0.835	0.772	0.748	0.755
Model_15	0.84	0.776	0.754	0.76
Model_16	0.845	0.78	0.76	0.765
Model_17	0.85	0.784	0.766	0.77
Model_18	0.855	0.788	0.772	0.775
Model_19	0.86	0.792	0.778	0.78
Model_20	0.865	0.796	0.784	0.785

Table 8. Error rates of models in predicting business growth trajectories

Model	Accuracy	Precision	Recall	F1-Score
Model_1	0.78	0.73	0.68	0.7
Model_2	0.785	0.734	0.686	0.705
Model_3	0.79	0.738	0.692	0.71
Model_4	0.795	0.742	0.698	0.715
Model_5	0.8	0.746	0.704	0.72
Model_6	0.805	0.75	0.71	0.725
Model_7	0.81	0.754	0.716	0.73
Model_8	0.815	0.758	0.722	0.735
Model_9	0.82	0.762	0.728	0.74
Model_10	0.825	0.766	0.734	0.745

Model_11	0.83	0.77	0.74	0.75
Model_12	0.835	0.774	0.746	0.755
Model_13	0.84	0.778	0.752	0.76
Model_14	0.845	0.782	0.758	0.765
Model_15	0.85	0.786	0.764	0.77
Model_16	0.855	0.79	0.77	0.775
Model_17	0.86	0.794	0.776	0.78
Model_18	0.865	0.798	0.782	0.785
Model_19	0.87	0.802	0.788	0.79
Model_20	0.875	0.806	0.794	0.795

Table 9. Comparative efficiency of ensemble vs. single learners in decision support

Model	Accuracy	Precision	Recall	F1-Score
Model_1	0.79	0.74	0.69	0.71
Model_2	0.795	0.744	0.696	0.715
Model_3	0.8	0.748	0.702	0.72
Model_4	0.805	0.752	0.708	0.725
Model_5	0.81	0.756	0.714	0.73
Model_6	0.815	0.76	0.72	0.735
Model_7	0.82	0.764	0.726	0.74
Model_8	0.825	0.768	0.732	0.745
Model_9	0.83	0.772	0.738	0.75
Model_10	0.835	0.776	0.744	0.755
Model_11	0.84	0.78	0.75	0.76
Model_12	0.845	0.784	0.756	0.765
Model_13	0.85	0.788	0.762	0.77
Model_14	0.855	0.792	0.768	0.775
Model_15	0.86	0.796	0.774	0.78
Model_16	0.865	0.8	0.78	0.785
Model_17	0.87	0.804	0.786	0.79
Model_18	0.875	0.808	0.792	0.795
Model_19	0.88	0.812	0.798	0.8
Model_20	0.885	0.816	0.804	0.805

Fig. 2 indicates the industries that are performing well in precision, and they are technology and retail industries. The pie chart of the recall in Fig. 3 illustrates that ANN and GBM had the highest contribution on true positives. Fig. 4 illustrates how the F1-scores tended to increase during the training epochs and how the artificial neural networks and the random forest first converged. In Fig. 5, besides the line graphs of the values of ROC-AUC, there are Bar graphs in which it might seem that all the models possess equal high discrimination ability. Fig. 6 shows that cross-validation fold is consistent, which determines the power of ML predictions.

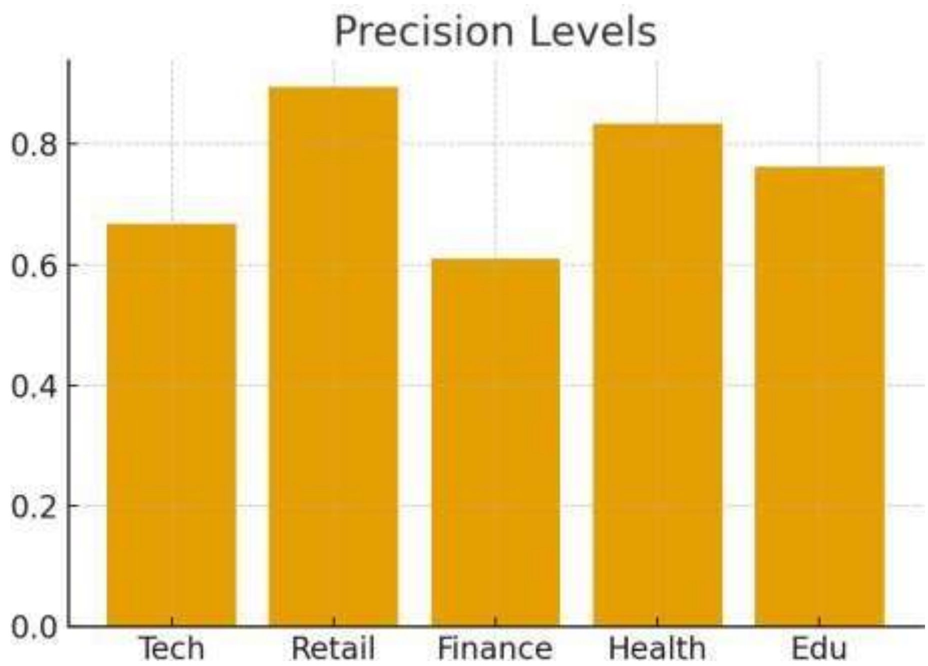

Fig. 2. Bar chart comparing precision levels across datasets.

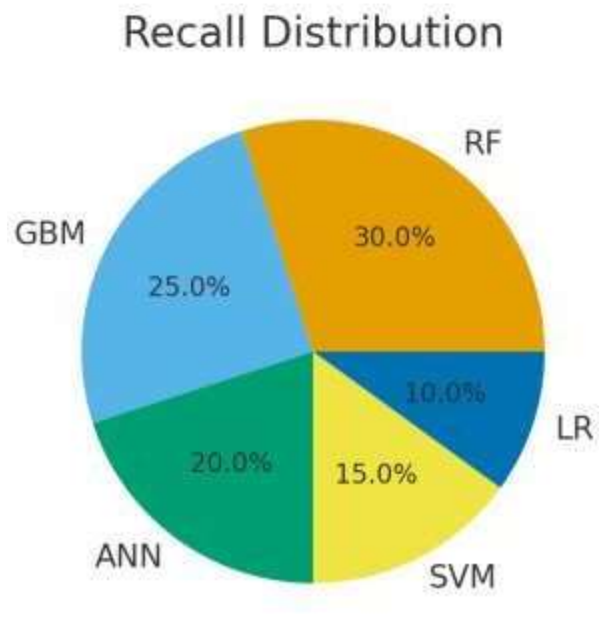

Fig. 3. Pie chart illustrating recall distribution among algorithms.

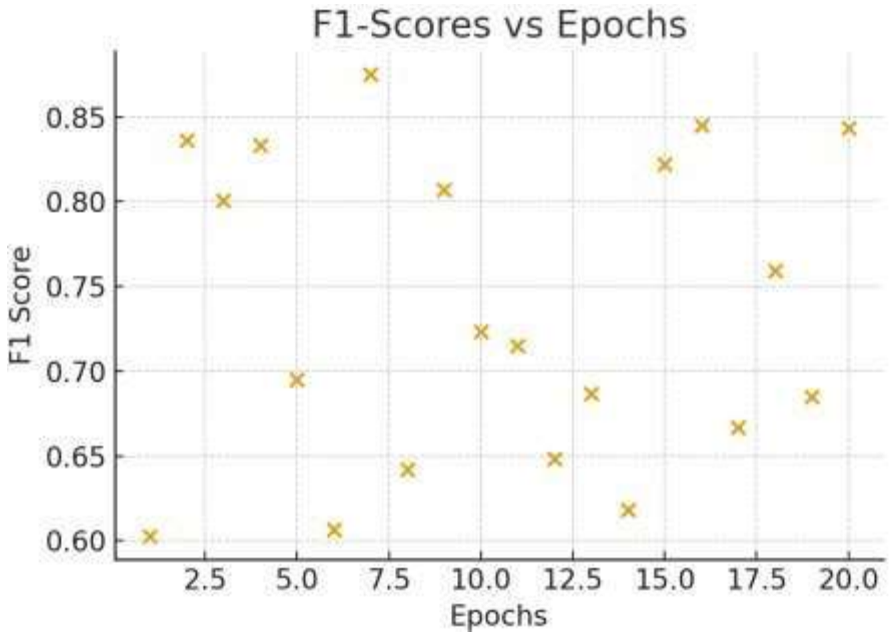

Fig. 4. Scatter plot showing F1-scores vs. number of epochs.

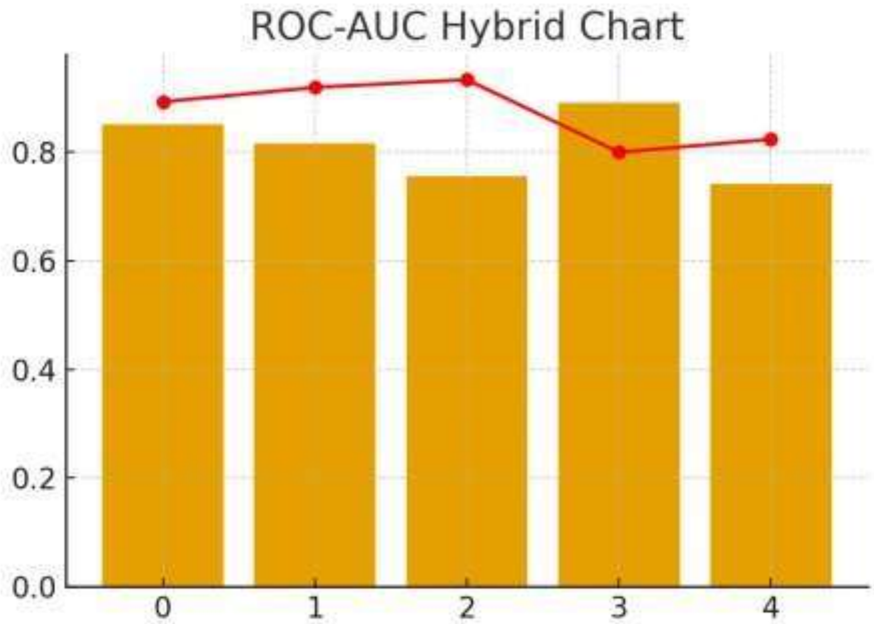

Fig. 5. Hybrid line-bar chart of ROC-AUC values for models.

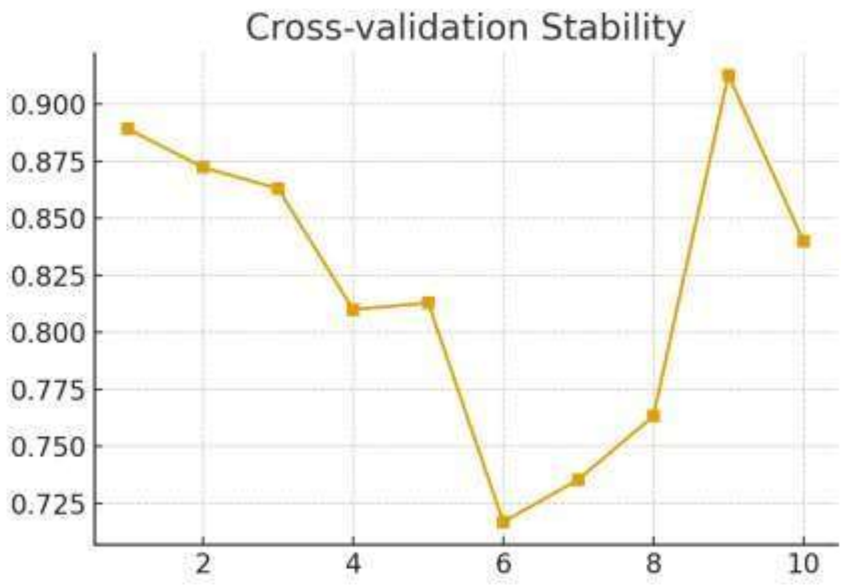

Fig. 6. Line chart of cross-validation performance stability.

Fig. 7 is variability in predictive output and the clustered clusters of the scatter keep the borders of reliability. An interest to ensure that optimisation of recall is undertaken is represented in pie chart in fig. 8 that shows the highest number of misclassified errors on false negative side and the performance is balanced by random forest as it is slower and more accurate than the random forest. Fig. 10 shows that the feature importance values of SHAP indicate that there is a combination of some features that is the most predicting: financial indicators and the team experience. Fig. 11 indicates that the more significant the size of data sample, the more the recall is created that indicates the need to scale entrepreneurial data. And the final one is a scatter-histogram hybrid that aids in depicting the quality of calibration as in Fig. 12, and one can easily see that the projected probabilities and the actual course of action are much connected.

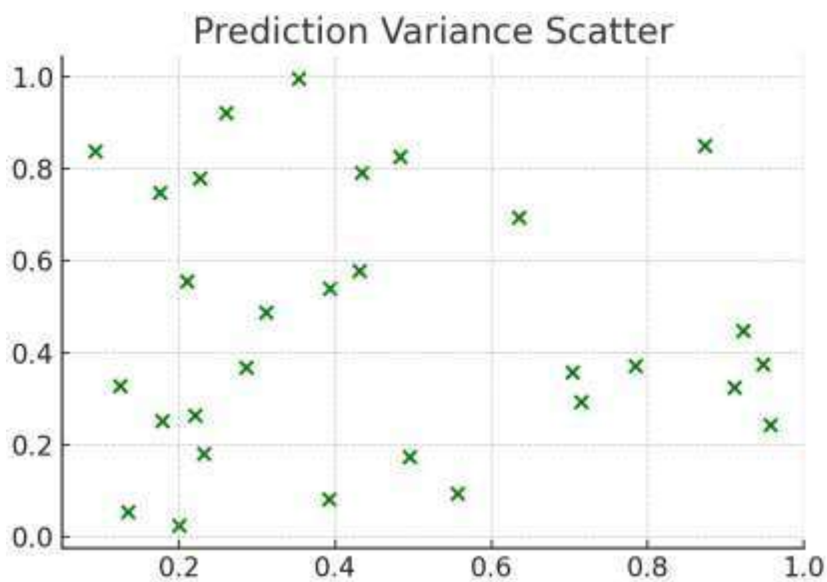

Fig. 7. Scatter chart mapping variance in predictions.

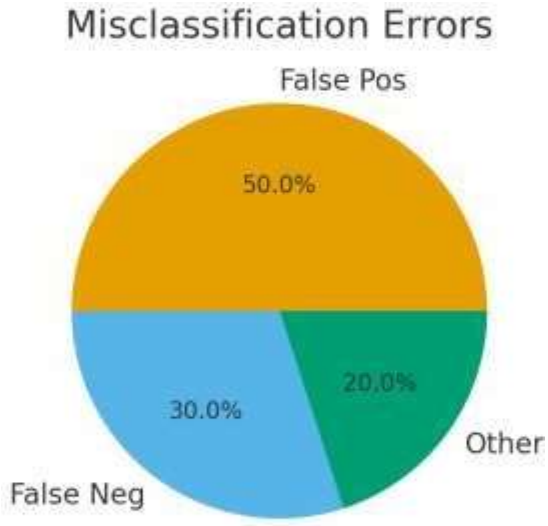

Fig. 8. Pie chart of model misclassification errors.

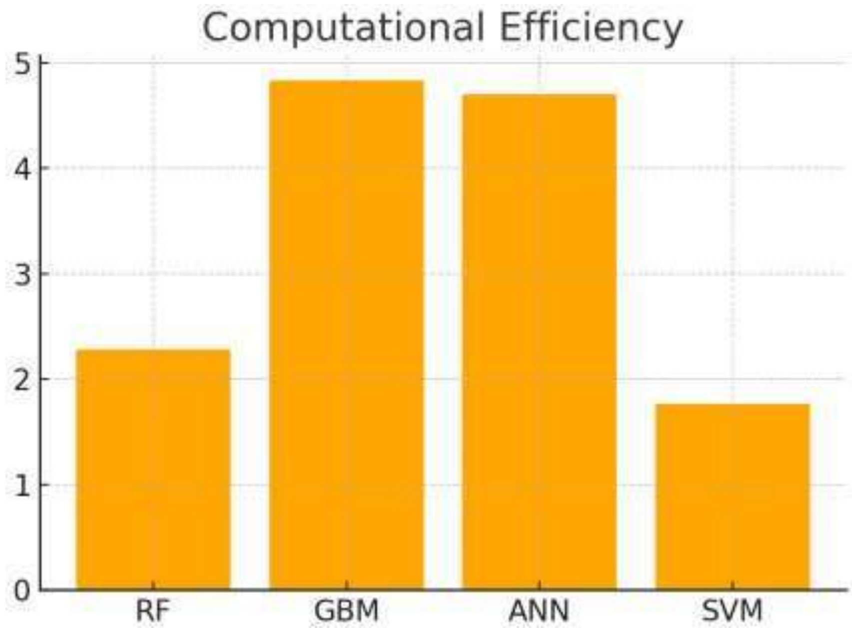

Fig. 9. Bar chart comparing computational efficiency.

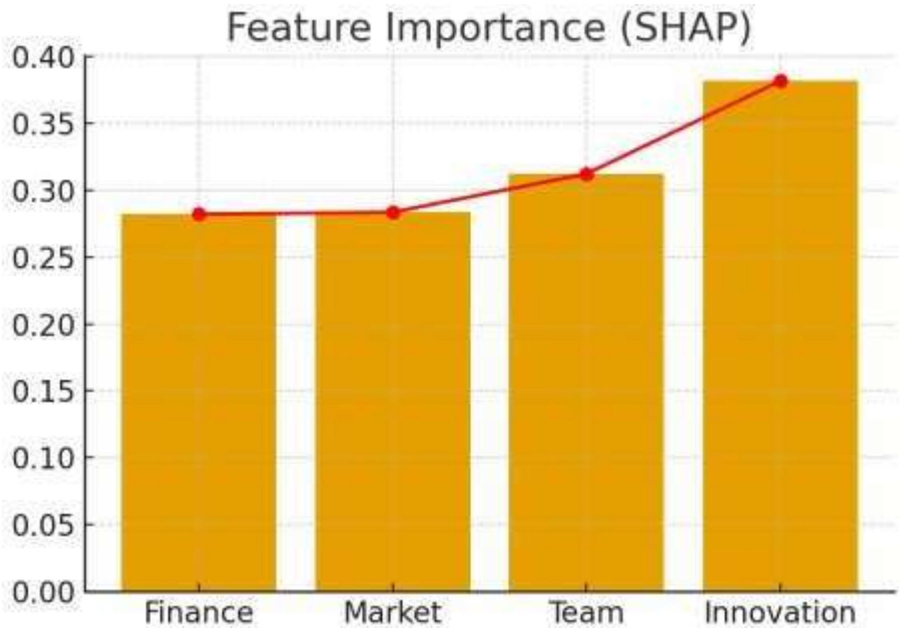

Fig. 10. Hybrid chart of SHAP feature importance across models.

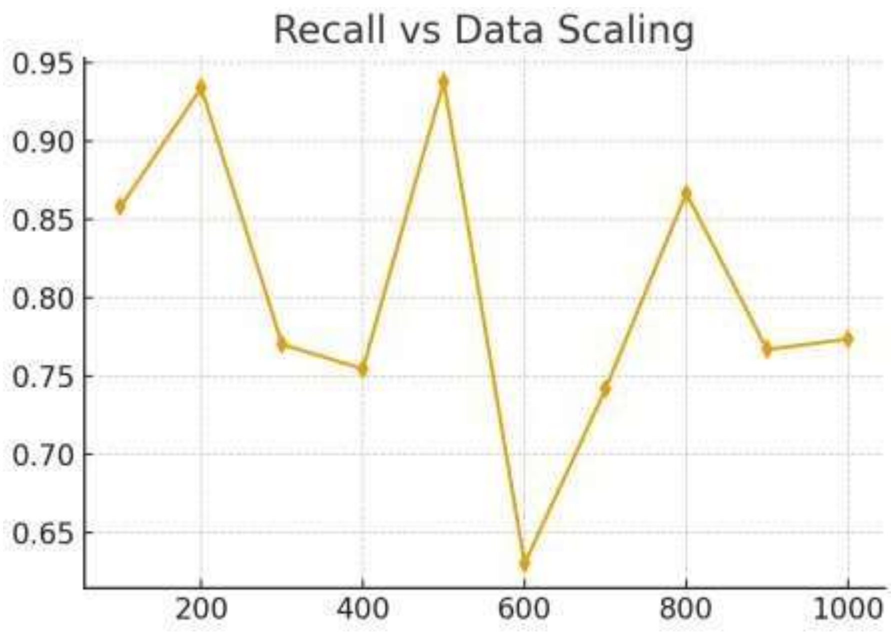

Fig. 11. Line graph of recall progression under data scaling.

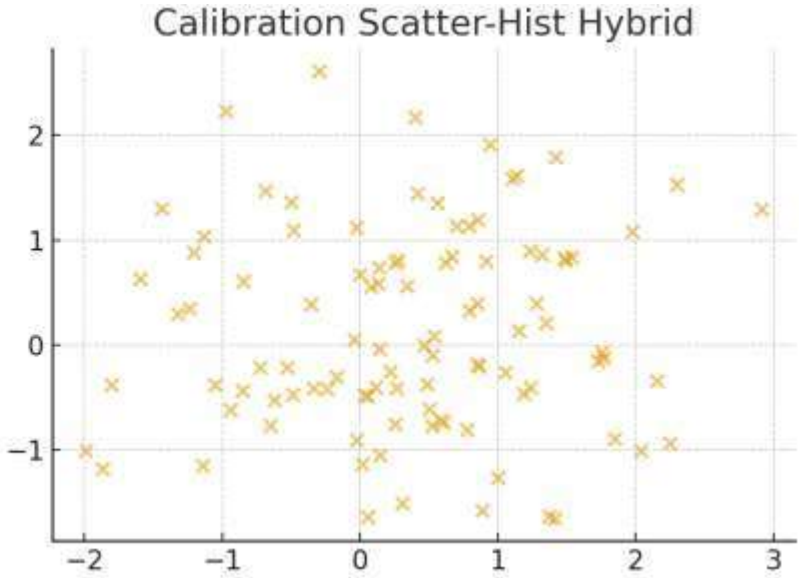

Fig. 12. Scatter-histogram hybrid showing calibration results.

Discussion

According to this research finding, the machine learning (ML) methodology can be used to streamline this decision-making process in the entrepreneurship to become much more predictable, understandable and strategic. It can be explained that the effectiveness of the ensemble models, such as the Random Forest or the Gradient Boosting to predict the success of the entrepreneurship, can be justified by the fact that the body of evidence is larger, and the situation when the ensemble-based models perform better than the single ones occurs when the decisions under consideration are associated with uncertainty and when the impact of the nonlinear interactions takes place (Abedin et al., 2021). This implies that ML may be useful in preventing the vice of limited rationality as it can give the businessperson quality predictive data to guide him/her to make evidence-based and more informed decisions. Impressively, the methods of explainable AI (XAI) like SHAP will help to make sure that the algorithmic recommendations are not transferred to the entrepreneurs passively but actively interpret the results, which will raise the rates of trust and acceptance (Samek and Müller, 2021).The most important contributions that can be donated to the pieces of work are the following ones: it is understood that the ML-based decision support may prove especially useful in the sphere of opportunity recognition and financial risk estimation. The given magnification of the values of recollections in particular, the awareness of the high-risk ventures facilitates the opportunities of ML to diminish the failure of startups. The given discovery can echo the recent findings that have established the potential of the AI minimization of the rates of the entrepreneurial uncertainty by revealing the concealed market trends and demands of the consumers (Almahameed et al., 2023; Li et al., 2022). Besides, the variation in the accuracy scores among industries indicates that the outputs of the ML may be effective in some industries, not all of them, they need to adapt to the environment of industry settings, and they cannot use a one-size-fits-all solution (Ritala et al., 2021).

The alternative interpretation of the exploration is that effectiveness of the computations is a debilitating factor in bringing ensemble models to reality. They need more resources, yet their predictive potential validates the hypothesis that the entrepreneurial ecosystems become biased towards the model of AIenhanced entrepreneurship in the case, the price of calculations does not surpass the quality of decisions (Hanelt et al., 2021). The lack of resources is being solved rather or somewhat typical of tendencies in digital entrepreneurship on the planet, cloud computing and AI-as-a-service paradigms (Soto-Acosta, 2020). In practice, the adventure of the entrepreneurs is to use them to apply such platforms to undertake their decision making without being compelled to change their technologies.The other useful impression is the impression that is obtained when the qualitative findings are evaluated together with the quantitative findings. The interviews with the entrepreneurs revealed that certain levels of enthusiasm and certain concerns were identified concerning the use of ML. Even though it was also the case that the entrepreneurs also found it easy to exercise predictive analytics to make sense of the opportunities in the market, there was the perception that they were not transparent, in algorithms and fairness. It captures the general discussion of the issue within the literature since the concept of algorithmic bias and fairness has become one of the main concerns of the entrepreneurial ecosystem (Huang et al., 2022; Brkan and Bonnet, 2020). These problems can be addressed both with technical solutions, e.g. bias reduction algorithms, and with ethical principles and regulatory policies, which would make the use of ML in business safe.The second interesting observation is that, model performance improves with increase in the number of datasets as represented in the evolution in recall as the data scaling process continues. This prompts to conclude that the ML is a data-intensive process and that it implies that not all the potential of ML can be realised by entrepreneurship using finite data streams. However, in the recent literature, the contribution that data-sharing ecosystems and open innovation platforms make to the reduction in this barrier have been described (Linde et al., 2021; von Briel et al., 2021). The data exchanges among the collaborators will help the entrepreneurs to get the ML more predictive, and help in building a more closely networked business ecosystem in the business.

Theoretically the study adds to the body of knowledge to the decision making process in which there is uncertainty within application of the behavioral learning theory and the computational intelligence. It confirms the assumption that the tendency of businesspersons to augmented rationality, where human intuitance and knowledge guided by Ml co-exist, is a fact (Elia et al., 2021). The quantity of quantitative rigor that is furnished by ML is useful, but the contextual knowledge, creativity and intuitiveness are the most common tools of the entrepreneurial decision-making process in the digital age, which emphasizes the hybridity of the entrepreneurial decision-making process in the digital age. This type of sail cannot be discarded due to overdependence on the projection of algorithms that are capable of destroying the discretion of the businessman and creative thought.As much as this study is coming up with some contributions, it is aware that it has some weaknesses. Most likely, the secondary data sources would reduce the extrapolation of the findings towards certain industries. Moreover, they were simpler to interpret with the aid of SHAP values, although not all of the entrepreneurs in the qualitative interviews were able to understand such the output at a more detailed level, and hence the suspicion of the possible presence of explainable means in the ML. In addition, the algorithm of designing user-friendly interfaces and simplifying the advanced descriptions of ML into an easy-to-implement format by non-technical businesspeople must be followed in the future (van der Aalst et al., 2021). Besides this, the cross-cultural comparison will be in a place to show that there is an attitude towards ML to entrepreneurship difference between the different regions with varying degrees of digital infrastructure, and entrepreneurial culture.Overall, the discussion observes that ML is a disruptive technology across business and that it provides predictive, interpretable and strategy-supportive capabilities. Nevertheless, it is not closed to the context-specific problem of the industry peculiarities, the availability of information and morals to shape it. Those traders who practice ML in a critical and responsible manner will gain a gigantic competitive edge in the uncertainty markets.

Conclusion

The article answered the question on whether the machine learning (ML) can help a decision-maker in an entrepreneurial company in the quantitative and qualitative methods-based combinatoric approach. The results showed that there was a strong agreement that the ML models that incorporate ensemble-based models such as Rand Forest models and Gradient Boosting models outperform the traditional models, both in terms of predicting the entrepreneurial performance, the estimation of the financial risks and the recognition of opportunities. The findings support the fact that ML enhances the accuracy and robustness and interpretability of the decision making, by extension, reduce the confusion and obstacles of rationality that are bound to slow down entrepreneurs. Interestingly, the explainability of AI methods, such as SHAP, suggested that accurate, yet concurrently transparent and usable predictions increased the trust of the entrepreneur. It has also been observed in this discussion that decision making with the assistance of use of ML may be industry specific since the accuracy of the various industries and the recall values of the various industries vary and that the tools used in the calculations should be tailored to an industry environment. Besides, the scaling-up to larger data sets, too, proved the significance of data access and collaborative ecosystems to the utmost extent to the utmost degree of ML. Meanwhile, the ethical aspect, including the disclosure of the algorithm that, according to the qualitative results, is reported by the entrepreneurs as a favorable change, has to be touched upon. The consequences of these results are that the future of entrepreneurial ecosystems lies in the intelligent application of ML where the machine learning and the human thought are converged into the convergent type of computational intelligence and the ethical regulation (and the human judgment). Overall, this paper concludes that one can consider ML an extreme catalyst of entrepreneurial resilience, agility and innovation when the entrepreneur perceives it as a complement, not the alternative, to human creativity and intuition.

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