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Rural Small Business Entrepreneurship Strategy Analysis with Optimization in Cooperation Industry Using Evolutionary Game Theory

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ABSTRACT:

America is becoming more divided between its rural and urban areas on a political and economic level. By boosting resilience to economic shocks, generating jobs, and quickening economic growth, entrepreneurship can assist rural communities in catching up. In contrast to metropolitan areas, there is little information available about business formation in rural areas. This research proposes novel technique in cooperation strategies based on rural small business entrepreneurship using game theory with machine learning model in conflict optimization. Here the small business entrepreneurship strategy analysis using support vector adversarial gradient game theory model. then the optimization has been carried using multi agent regression convolutional Q-learning. Development method of the current rural industries is recorded from standpoint of entrepreneurship, global classic practical experience of digitising rural industries is investigated. F-1 score, average precision, recall, efficiency, and prediction accuracy have all been examined through experimental study. Using machine learning, we predict small businesses' active participation in community resilience. We find that performance of model is significantly enhanced by addition of social capital predictors. The proposed model attained prediction accuracy of 97%, F-1 score of 95%, average precision of 93%, recall of 92%, efficiency of 94%.

Keywords: cooperation strategies, small business entrepreneurship, game theory, machine learning model, conflict optimization

1. Introduction

A major application for social and economic advancement of rural communities and agriculture is digital rural. Digital villages are a reflection of modernization as well as transformation processes occurring in agriculture and rural areas as a result of farmers' increased access to modern information capabilities. The long-term growth and high quality of rural economy are significantly impacted by promotion of digital rural construction, which also helps with digital China construction and rural regeneration [1]. A new course in China's rural regeneration and agricultural modernization development is currently being paved by the country's aggressive development of a digital economy as well as creation of a digital countryside. With a population of 20.7%, the rural sector's main economic activity is agriculture, and its access to funding through microcredits from microfinance organisations is restricted. Since there is little to no information in this field, new tools to boost assertiveness are needed. In addition, just 43% of the nation's population has financial inclusion, which is a low proportion. In the Puno region, where 46.22% of people live in rural areas, this study was carried out using a sample of 15,015 microfinance clients who had at least one agricultural product microcredit in 2017. Issuing of microcredit is contingent upon the evaluator's skills and is based on a predetermined assessment process that is carried out by rural credit analysts using customer data to assess willingness and payment capacity. The financial capacity assessment and client background are the first steps in this procedure. Data analysis is then conducted, and the client acceptance—that is, whether or not credits will be issued and under what circumstances—is the last step. Due to the likelihood of loan obligations being broken, which could result in losses for microfinance or financial institutions, banks have put in place a number of risk management methods or systems to lower credit risk. Its goal is to comprehend the consumer's solvency; models that rely on criteria are applied by skilled advisors, subjective methods are frequently used. Other AI-based computational techniques, such machine learning, which enables supervised and unsupervised computer learning based on experience, can be applied to carry out more assertive client evaluations [4]. The default rate, which has been reported to the regulatory body, is a reflection of the microfinance institution's analysis of customers who have missed or postponed payments. The default rate in the last three years was 6.1% in 2016, 6.3% in 2017, and 6.5% in 2015. This range suggests a lack of aggression in the microlending process, even in the presence of highly qualified and experienced professionals. Utilizing a new method to identify method with best assertiveness level, we will start with the definition of rural variables. It also creates major obstacles for creating and capturing value in business models (BMs) [5]. Today, there is a growing use of machine learning (ML) to support organisational activities due to widespread availability of data, notable advancements in telecommunications technology, and the democratisation of mobile models, Internet of Things (IoT), cloud storage. Previously unthinkable business models may become possible with the application of machine learning. It takes enormous resources to implement ML technologies inside a BM, and it is not the same as setting up a BM with traditional technology. Some startups use ML methods to create and capture value on a never-before-seen scale. Waze, Google, Facebook, and Amazon are a few prominent examples. But not every startup employing ML technologies is able to generate and seize value in this manner [6].

2. Related works

Small businesses are the small acorns from which future multinational corporations sprout, and they are the primary providers of disruptive innovation and employment (International Finance Corporation, 2019). Because of the important role small businesses play in economic development, there has been an increase in interest in their growth throughout the years. Extensive study on business expansion has been undertaken over the years, and several theoretical models for explaining this phenomena have been proposed [7]. The Stochastic hypothesis, proposed by [8], is one of the most widely accepted theories of company growth over time.In the study of DL technology in rural development and construction, work [8] used an enhanced CNN to extract data from remote sensing images of rural buildings automatically. Author [9] used DL methods and machine vision to recognise scenes in rural tourism. Based on data shown above, picture recognition using the DL approach is successful. Still, there are drawbacks. The technological and financial barriers of creating a digital hamlet are not specifically covered in this study. Additionally, it doesn't address the problems with resources and environment brought up by the development of digital towns. Work [10] holds that an organization's ability to reconcile a business model prototype with its surroundings depends on strategic flexibility as well as integration capabilities of its enterprise resources. The author [11] found that executive support is the main factor driving the acceleration of BMI and that BMI cannot be realised without it. The impact of technological innovation, the market environment, other stakeholders are examined in the second type of study, which starts with the external environment of the firm. For example, [12] discovered that market orientation and market opportunity were crucial in BMI, that customers' consumption habits as well as demand levels led firms to consistently develop their business models. Work [13] believed that market competitiveness as well as business crisis pressure were essential motivators for organisations to seek out innovation opportunities, as well as an important motivator for firms to implement BMI. According to an entrepreneur performs his or her function appropriately and successfully in a responsible manner, which necessitates the capacity to possess entrepreneurial competencies, also known as entrepreneurial skills. Work [14] discovered that managerial and entrepreneurial abilities play a key role in the success of female entrepreneurs. It covers finance, human resource management, production and operation operations, creativity, innovation, and product marketing. Author [15], who conducted research in Utah, discovered that entrepreneurs must identify and prioritise entrepreneurial, technical, and managerial functions in order to succeed. After conducting their research, Mitchelmore and Rowley postulated that managerial competencies—which encompass functional and organisational competencies—are essential to the development and long-term viability of entrepreneurs. Sixteen areas of similar capability were identified by work [16], including strategic planning, marketing opportunities, and good management—all of which are essential for the long-term success of an entrepreneurial venture. Six competency areas—organization, concepts, commitment, opportunity, and interpersonal interaction—that are essential to their performance were discovered by work [17] carried out as part of their study. One of the most crucial components identified as enhancing project performance in a study by [18] was being ready to take on risks. This may be connected to the risk-taking aspects of entrepreneurial orientation. Over time, it has been shown that innovation capability, another aspect of entrepreneurial attitude, contributes to project success [19]. A favourable team environment for innovation leads to enhanced project performance: teams with a positive orientation for innovativeness complete projects faster than teams without it [20]. Teams often need creativity to succeed in a project. Proactiveness is another facet of an entrepreneurial mindset. According to Work [21], project managers should be proactive as this might contribute to the project's success. Additionally, the research on project management has highlighted self-efficacy—which is associated with an entrepreneurial attitude—as potentially influencing a number of project performance, commitment, and knowledge sharing elements. Because of this, there is sufficient data in the literature on project management to demonstrate that an entrepreneurial mindset and project success are positively correlated [22].

3.Small business entrepreneurship strategy analysis using support vector adversarial gradient game theory model (SVAG-GT):

The emergence of rural e-commerce entrepreneurship ecosystem involves three types of game players: e-commerce platform (EP), enterprise individuals (EIs), government (G). Because 3 parties have partial symmetrical knowledge, determining each of their behaviour probabilities is challenging. Because all parties are limited by logic, the three parties must constantly learn and change, revise plans, and repeat the game before achieving a stability strategy. E-commerce platform has two strategies: active participation and passive participation, whereas entrepreneurship individuals' behaviour strategies include accepting and refusing services, government's behaviour strategies include active and passive participation. The functions of time t are α, β, and γ ∈ [0, 1], which correspond to the probability of EP's active involvement, EIs accepting services, G's active participation, respectively. The three players have three initial intentions, denoted as α0, β0, and γ0, respectively, they all dynamically modify their game strategy throughout time t. Real number field R ={(α, β, })|α, β, } ∈ [0, 1]} has nine equilibrium points that can meet the following requirements if F(α) = F(β)= F(γ) = 0. This is in accordance with the evolutionary game theory by eqn (1)

$$\begin{cases} \alpha(b_4-b_5)+(\alpha-\alpha\gamma+\gamma)\lambda_1 s_1+\alpha\gamma b_3=0 \\ (d_1-c_1)+\beta b_2+\beta\gamma kp-b_0=0 \\ (1-\alpha\beta)kp-\beta(\alpha-1)\lambda_2 s_2+\beta(\alpha-1)\lambda_1 s_1-c_2=0 \end{cases}$$

$$\mathrm{F}'(\alpha^*)=(1-2\alpha)[(d_1-c_1)+\beta\gamma kp+\beta b_2-b_0]$$

$$\mathrm{F}'(\beta^*)=(1-2\beta)[\alpha(b_4-b_5)+\alpha\gamma b_3+(\alpha+\gamma-\alpha\gamma)\lambda_1 s_1]$$

$$\mathrm{F}'(\gamma)=(1-2\gamma)[(1-\alpha\beta)kp+\beta(\alpha-1)\lambda_1 s_1-\beta(\alpha-1)\lambda_2 s_2-c_2] \quad (1)$$

In general, learning is the process of utilising data to generate a hypothesis that performs better than an a priori hypothesis generated in absence of evidence. The hypothesis will be shown as functions of the type f: X → Y, which map a class y ∈ Y to an input sample point x ∈ X. This indicates that a hypothesis f produces a prediction in output space Y given an observation from the input space X. The output space for binary classification is Y = {−1,+1} by eqn (2)

$$\min_{\mathbf{w},b,\xi}\frac{1}{2}\mathbf{w}^\top\mathbf{w}+C\sum_{i=1}^{n}\xi$$

$$\text{s. t. } \forall i=1,\dots,n\ y_i(\mathbf{w}^\top\mathbf{x}_i+b)\geq 1-\xi_i \text{ and } \xi_i\geq 0, \quad (2)$$

where variables ξi indicate the degree to which the samples, xi, violate the margin, and the margin is maximised by minimising 1 2w >w. The trade-off between maximising the margin and minimising sum of slack violation mistakes is adjusted by the parameter C. Although primal is solved directly, it is usually addressed via its dual issue expressed in terms of Lagrange multipliers, αi, which are limited to 0 ≤ αi ≤ C for i = 1,...,n, ∑ n i=1 αiyi = 0. Rather of increasing in dimensionality with the feature space, the computational cost of solving dual increases with size of training data. Additionally, in dual formulation, slack variables as well as data are implicitly represented. Using the Lagrangian multipliers method, the dual issue is obtained as a matrix by eqn (3)

$$\min_{\alpha}\frac{1}{2}\alpha^\top\mathbf{Q}\alpha-\mathbf{1}_n^\top\alpha$$

$$\text{s. t. } \sum_{i=1}^{n}\alpha_i y_i=0 \text{ and } \forall i=1,\dots,n\ 0\leq\alpha_i\leq C \quad (3)$$

where Q, Hadamard product of K and yy>, is equal to K ⋨ yy>. and a vector of n ones is 1n. By using a kernel function, which is an implicit inner product from alternative feature space, SVMs are extended to more complicated feature spaces through the use of a kernel matrix. In other words, if a function φ: X → Φ translates training samples into a higher-dimensional feature space, then κ(xi,xj) = φ(xi) >φ(xj) is kernel function that corresponds to space and is used to compute Ki j. Therefore, only relevant kernel function and not φ itself need to be known directly. Additionally, dual issue and associated KKT conditions reveal intriguing SVM features. First, w, the normal vector of the ideal primal hyperplane, is a linear mixture of the training samples, or w = ∑ n i=1 αiyixi. Second, only samples that fall on or within margin of hyperplane have a nonzero α-value, indicating that dual solution is sparse. Consequently, one need only be directly aware of the pertinent kernel function and not of φ itself. Moreover, dual issue as well as related KKT conditions unveil interesting characteristics of SVM. w = ∑ n i=1 αiyixi represents normal vector of the ideal primal hyperplane, which is a linear mixing of training samples. Dual solution is sparse because samples with a nonzero α-value only lie on or near hyperplane's edge. Hence, in event where αi = 0, corresponding sample xi is deemed non-support vector since it is accurately identified, sits outside of margin. i th sample is an error vector and violates margin (yi(w >xi +b) < 1) if αi = C. Lastly, i th sample is a support vector that sits exactly on the margin if 0 < αi < C (that is, yi(w >xi +b) = 1). Consequently, yi −w >xi can be averaged over the support vectors to find the ideal displacement, b. We suppose, without sacrificing generality, that the Byzantine vectors B1,..., Bf fill the last f positions in the KR argument list, meaning that KR = KR(V1,..., Vn−f, B1,..., Bf). Let i∗ represent the vector's index that the Krum function selected. We concentrate on (α, f)-Byzantine resilience condition (i) (Definition 1). First, let us consider the scenario in which a vector proposed by an appropriate process is Vi∗ = Vi ∈ {V1,..., Vn−f }. In order to determine that i → j, the vector Vi must first be compared to the average of the correct vectors Vj. Let the number of such Vj's be \c(i) by eqn (4)

$$\mathbb{E}\left\|V_i - \frac{1}{\delta_c(i)}\sum_{i\rightarrow \text{ coerect } j} V_j\right\|^2 \leq \frac{1}{\delta_c(i)}\sum_{i\rightarrow \text{ coerect } j} \mathbb{E}\|V_i - V_j\|^2 \leq 2d\sigma^2 \qquad (4)$$

The final inequality is valid since the first inequality's right-hand side only includes vectors that are offered by legitimate processes, which are independent of one another and adhere to G's distribution. Now consider the situation where a vector suggested by a Byzantine procedure is Vi∗ = Bk ∈ {B1,..., Bf }. Since k reduces the score, it follows that for all indices i of the vectors suggested by proper procedures by eqn (5)

$$\sum_{k\rightarrow \text{ correct } j} \|B_k - V_j\|^2 + \sum_{k\rightarrow \text{ byz } l} \|B_k - B_l\|^2 \leq \sum_{i\rightarrow \text{ correct } j} \|V_i - V_j\|^2 + \sum_{i\rightarrow \text{ byz } l} \|V_i - B_l\|^2 \quad (5)$$

The same conditions as in the non-convex convergence analysis apply to (i) through (iv). The condition (v), which states that the cost function Q is "convex enough" beyond a certain horizon—that is, that the gradient's direction is sufficiently near to the direction of the parameter vector x—is a little stronger than the equivalent requirement. For the proper workers to meet condition (iv), the gradient estimator they use must be sufficiently exact, meaning that the local standard deviation must be small compared to the gradient norm. Naturally, the gradient's norm gets closer to zero at saddle and extremal locations. In actuality, the greatest angle between the gradient ∆Q and the vector selected by the Krum function is determined by the ratio η(n, f) · √ d · σ/k∆Qk. Byzantine workers may use the noise (measured by σ) in the gradient estimator G to influence the parameter server selection in the regions where k∇Qk < η(n, f) · √ d · σ. As a result, Proposition 2 should be understood as follows: when Byzantine workers are present, the parameter vector xt nearly certainly approaches a basin at sites where the cost landscape is "almost flat," or where the gradient is minimal (k∇Qk < η(n, f) · √ d · σ). Take note that the convergence study is predicated solely on the (α, f)-Byzantine resilience of function KR. Proposition 2's full proof is postponed until the supplemental information.

A random variable x ∈ R n, which can be either positive or negative, is available to the adversary. □ ∈ {−1, +1} designates the class to which x belongs. It is a binary random variable with P{□ = +1} = 1 − P{θ = −1} = α > 0. Assuming that θ = +1, random variable x is Gaussian with mean μ+ ∈ R n and a covariance matrix Σ+ ≻ 0, and assuming that θ = −1, it is Gaussian with mean μ− ∈ R n and a covariance matrix Σ− ≻ 0. Annotation While A ≻ 0 indicates that A is positive semi-definite, A ≻ 0 implies that A is a symmetric positive definite matrix. Classifier receives a message from the opponent, y ∈ R n. This message could or might not be accurate. It is assumed that y comes after by eqn (6)

$$\underset{\bar{A},\bar{\mu}_w,R_w,Z',t}{\arg\max} \; -\alpha^{\top}(\bar{A}\mu_+ + \bar{\mu}_w) - \beta \qquad (6)$$

where w ∈ R m is a Gaussian random variable with mean μw ∈ R m and co-variance Σw < 0, and A ∈ R n×n is a weighting matrix. Let γ := (A, μw, Σw) represent the enemy's policy. The enemy's whole policy set is represented by Γ. That adversary may only be able to change data points that belong to positive class. There is always a constant sum in the adversarial classification game. Let (γ ∗, η∗) have the following parameters so that (1) and (2) hold with probability one by eqn (7)

$$A = \bar{A}/t_1, \mu_w = \bar{\mu}_w/t_1, \Sigma_w = R_w R_w^{\top}/t_1,$$
$$\alpha = \bar{\alpha}/\max\{\| \bar{\alpha} \|_\infty, |\bar{\beta}|\}, \beta = \bar{\beta}/\max\{\| \bar{\alpha} \|_\infty, |\bar{\beta}|\}$$

where (A, μw, Rw, Z′ , t1) is given by $y = \begin{cases} Ax + w, & \theta = +1, \\ x, & \theta = -1, \end{cases}$ (7)

The direction of the steepest fall in the parameter space to minimise the loss function is the negative gradient. On the other hand, the negative natural gradient is the steepest downward direction in the distribution space when distance is measured by KL divergence. As a result, the direction in the distribution space that the natural gradient describes will be independent of the parameterization decision, meaning that it will solely depend on the distribution that the parameter values produce, rather than the model's parameterization.

Optimization using multi agent regression convolutional Q-learning (MARCQL)

Frequently, the issue that needs to be resolved is denoted as a Markov Decision Process (MDP). With agent making decisions and the environment reacting to them by presenting the agent with new possibilities, MDP is a mathematical framework that maximises agents' decision-making in interactions with their surroundings. A state space (S) and an action space (A) make up an MDP. The agent is rewarded immediately at each time step t (Ra s = E[Rt+1 | St = s, At = a]) for carrying out action a ∈ A at state s ∈ S. Objective of MDP is to identify best course of action, or optimal policy π, in each state s that will ultimately maximise projected long-term return. P∞ i=0 γ iRt+1+i = Gt. The future reward's importance is represented by discount factor, γ ∈ [0, 1]. Based on agent's present state and environment, two types of policies regulate its actions. Deterministic policy (a = π(s)) is the first one. This suggests that agent's opportunity to intervene at the state level is limited. P π [a | s] = π(a | s) is the stochastic policy, which is the second policy. Based on the likelihood of the action at state s, the agent can choose from a number of different courses of action, with the result that P A π(a | s) = 1. Next state, s ′, is determined by transition probability function P when agent at state s behaves in accordance with policy π(a | s). The formula for the transition probability function is P a ss′ = P[s ′ | s, a]. According to policy π, expected return upon movement to state s is typically represented by a state-value function as eqn (8)

$$V^{\pi}(s) = \mathbb{E}[\mathcal{G}_t \mid \mathcal{S}_t = s]. \qquad (8)$$

Likelihood that the agent is in same state is indicated by this equation. Similar to this, action-value or q-value are frequently used to characterise expected return in state st following selection of action an in accordance with policy π. This indicates the likelihood that agent will behave in that situation. The Q-function yields q-value, and it is defined as eqn (9)

$$Q^{\pi}(s,a) = \mathbb{E}[\mathcal{G}_t \mid \mathcal{S}_t = s, \mathcal{A}_t = a] \qquad (9)$$

From eqn(10), we must obtain an optimal policy π ∗, which is given by, policy π dictates how agent acts at given state to attain optimum actions.

$$\pi^* = \arg\max_{\nabla} Q^*(s,a) \qquad (10)$$

The agent approximates the target value using maximum Q-value of the future state and immediate reward value since it is unknown in advance. To put it another way, yt = rt + γ max a 0∈A Qt(st+1, a 0). α lies between 0 and 1. is the rate of learning that characterises the degree of reliance between the new and previous information. The Q-learning approach keeps track of every state-action pair's Q-value in a look-up table. Consequently, tabular Q-learning is another name for it. Furthermore, it can guarantee convergence to the ideal value in the event that agent visits state-action pairs without end. Deep Q-learning network is trained with equally sampled data from experience pool, rather than real-time data. This technique might eliminate the sample-to-sample correlation. The other network is the target network. It is similar to the assessment network in structure, but has different parameters. In other words, max a 0∈A Qt(st+1, a 0) is estimated using the target network. Convolutional neural networks are used to approximate f, and the parameters θ are trained using a database of images I^{ = ¯I1,..., ¯In and accompanying annotations P¯ = {p{1,..., p{n}. To train f utilizing every annotated image, a Euclidean loss L(I,P; θ) = 1 2N PN k=1 ||f(Ik; θ) − p¯k||2 2 is typically used. For single component signals, first label indicates modulation type of signal, while second label is ‘‘empty’’, which is denoted by label value 9. Figure 1 depicts the structure of CNN after output portion is extended, based on signal label form presented in this research.

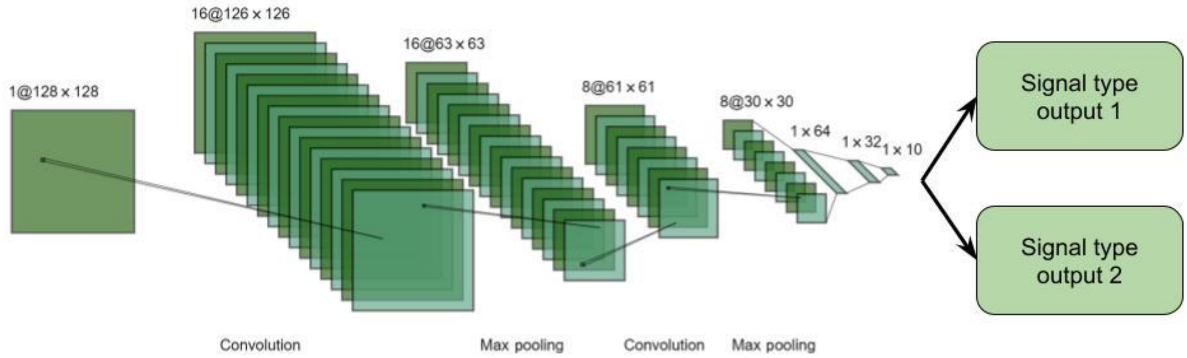

Figure 1. The structure of CNN after extending the output part

Just three convolutional layers and three pooling layers make up the convolution component of the CNN suggested in this work. Second, width of time-frequency curves in TFIs dictates the size of the convolutional kernel. Radar signal time-frequency curves in TFIs have a width of two to three pixels. In this study, the CNN's convolutional kernel size is designed to be 5 x 5 to capture subtle characteristics and variations of time-frequency curve trend. The second layer's 5 x 5 convolutional kernel produces a 21 × 21 feature map, necessitating padding in pooling layer of third layer. In average pooling in this study, edge padding processes might generate noise interference. Convolutional kernel size of second layer is set at 3 x 3 in order to remove padding. Feature maps generated by last pooling layer are vectorized into feature vectors after convolution and pooling operations. Following mapping of recognition results of two signal components to 2 fully linked layers, Softmax layer uses recognition results to convert them into probability values.

Solution, which is anticipated output for that set of output values (n), is connected to a particular set of input values (m) by a linear equation in the picture. The values in input and output are both numerical. To evaluate regression coefficients of trained data and ascertain relationship between test and train data, linear regression technique starts with testing and training data. The accuracy of the testing and training was calculated as an output. The linear regression flowchart is displayed in Figure 2.

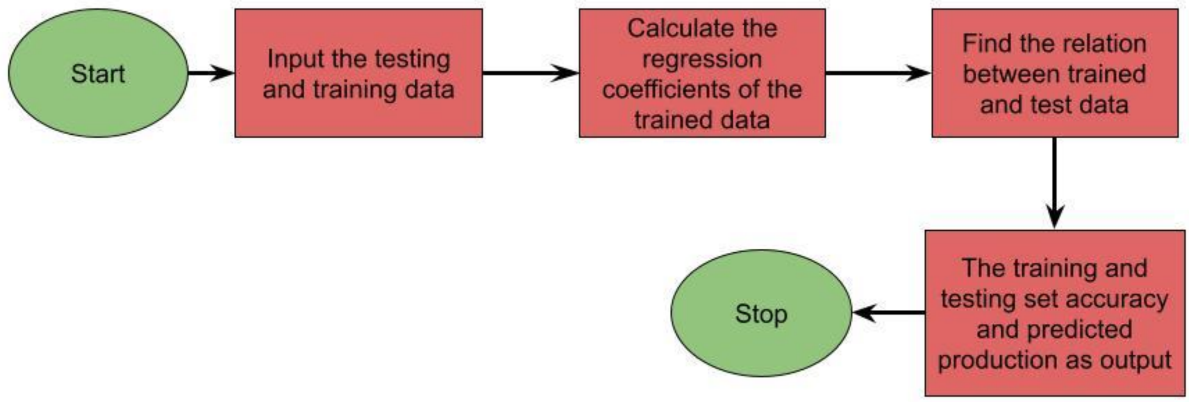

Figure-2 regression flow chart

Every input value or column in linear equation receives one scale factor, or coefficient, which is represented by the letter C. An additional coefficient, known as bias or intercept coefficient, is also appended, providing line with an additional degree of freedom. For instance, the form of the equation representation in a highly statistical method disadvantage by eqn (11)

$$y = \mathbf{C}0 + C1^{*}X \qquad (11)$$

These eleven combinations fall into two categories: those with cooperative policy and those without. In this work, 961 (31*31) Agent groups are simulated in the grid space using Netlogo software, where each Agent has four randomly allocated Agent games. The author established specific assignment matrix for I d = 5, Z = 10, F − Md = −1 in light of the situation. We can ascertain the location of the saddle point (1/6, 1/6) based on the results above. When combining cooperative strategies, I place special attention on analysing two scenarios: the stability of the combination of policies at a critical saddle point and the stability of the combination of policies after the group average. We exclusively analyse one scenario for non-cooperative strategy combinations: the stability of policy combinations following group averaging.

There are two sorts of value-sharing game models: value-sharing model that is controlled by dominant corporations and the value-sharing model that is acquired through negotiation. First, the value-sharing game method used by the large corporations looks like this: Top businesses determine a sales price, p, based on market demand in order to maximise the interests of both sides. Additionally, they offer a value-sharing coefficient, λ ($0 < \lambda < 1$), which denotes portion of the market terminal sales price benefit that will be distributed to small farmers. In order to ensure primary agricultural product supply, lower opportunity costs, promote small farmers' participation in the agricultural value chain, accomplish coordinated profit distribution, and enhance quality and efficiency, leading enterprises share λ of the value, with small farmers receiving the remaining value (1 - λ). Smallholders are responsible for the quality of their goods and receive the order (wholesale) price.

The leading enterprises no longer establish the value-sharing coefficient λ on their own; instead, small farmers and the leading enterprises negotiate to determine it. In order to guarantee a constant quality and output of agricultural raw resources, top enterprises have to make concessions. The two sides now discuss extensively before deciding on the share of value-sharing revenue based on market mechanism as well as game's outcome, rather than deciding on the amount of money alone. Small farmers will "vote with their feet" or even stop producing agricultural products, compelling firms to make concessions even though they may be at a disadvantage in the game. However, in order to avoid moral hazard and get consistent and respectably high agricultural output returns, small farmers need to adhere to established production requirements. In actuality, the two parties negotiate in order to reach a balance and the appropriate amount of value sharing through long-term cooperation.

4. Results and discussion

The Titan Xp, which has an Intel(R) Xeon(R) CPU running at 3.0GHz, 13GB of RAM, and an NVIDIA Tesla K80 GPU, has been used to train and test datasets. We utilised the necessary packages in addition to the PyCharm IDE. Each model was trained for a mere 10 epochs using a batch size of 16 and a learning rate of 0.01.

Dataset description: NCR-Stat: Small Business Survey: Information regarding small enterprises in the North Central Region was gathered by the NCRCRD. 1,287 small company owners' answers are included in the dataset; the replies cover a variety of topics, such as owner profiles and workplace health and wellness.

The database known as the OECD Structural and Demographic Business Statistics (SDBS) is a vital resource for evaluating the dynamics and industrial structure of OECD nations. At a very specific sectoral level, it offers a multitude of information, including, but not limited to, turnover, value-added, production, operational surplus, employment, labour expenses, and investment. An additional breakdown into size classes is included in addition to split by industrial sector, which includes services. Business demography data, such as enterprise birth, death, survival rates and quantity of high-growth businesses and gazelles, are also included in database. Size class dimension dataset and the business demography dataset together make up an outstanding resource for the OECD Entrepreneurship Indicators Programme (EIP).

The SHRUG is an India-specific Socioeconomic High-resolution Rural-Urban Geographic dataset. This is a new dataset with over 600,000 constant border geographic units that offers multidimensional socioeconomic data on India's cities, towns, and villages between 1990 and 2013. Additionally, data are combined with legislative constituency. The SHRUG is distinct in a number of ways from traditional sample datasets that are used to research changes in the socioeconomic conditions of developing nations. First off, the SHRUG is not a sampling; it is a census. It may therefore be expanded upon: any new census dataset that describes the entire universe of locations in India can be directly and minimally linked to the SHRUG at a high geographic resolution. On the other hand, sample surveys can only be connected with reliability at extremely high aggregation levels. The National Sample Survey, India's premier socioeconomic survey, does not consistently sample the same villages and is only representative at the state or district level. Although NSS panels are frequently built at the district level, no lower level of aggregation can be achieved because these panels are typically based on less than 100 households per district. As a result, they struggle to adequately convey the wide range of results among districts.

Table- 1 comparison between proposed and existing technique for multi plant disease detection dataset

Dataset	Techniques	Prediction accuracy	F-1 score	Average precision	Recall	Efficiency
NCRCRD	**DCNN**	77	78	76	78	78
	RL-QNN	85	83	80	80	83
	SVAG-GT_MARCQL	93	87	82	85	86
SDBS Dataset	**DCNN**	74	77	72	82	81
	RL-QNN	79	82	76	84	85
	SVAG-GT_MARCQL	89	88	85	89	89
SHRUG Dataset	**DCNN**	78	86	71	85	87
	RL-QNN	89	92	76	87	90

	SVAG-GT_ MARCQL	97	95	93	92	94

Table-1 shows analysis for multi plant disease detection dataset. Here the sports multi plant disease detection dataset analysed are NCRCRD , SDBSDataset and SHRUGDATASET in terms of Prediction accuracy, F-1 score, Average Precision, Recall, Efficiency.

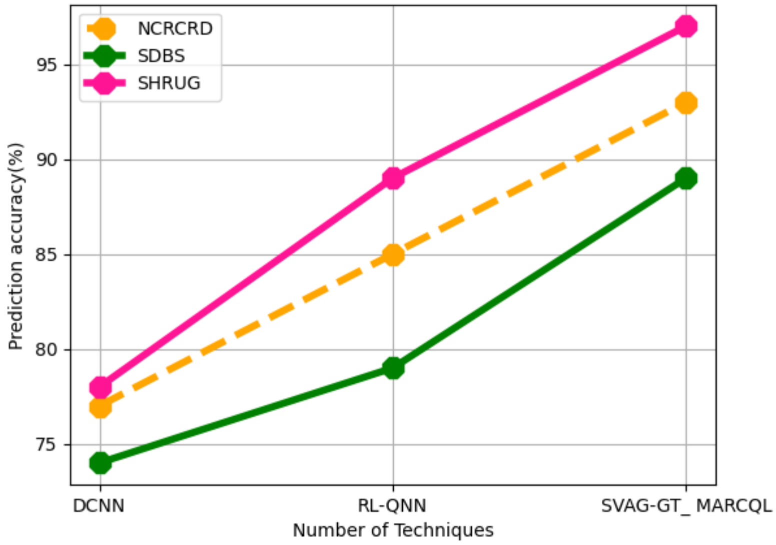

Figure-3comparison of Prediction accuracy

The analysis for prediction accuracy is displayed in Figure 3. Here, the proposed technique achieved 93% prediction accuracy, 77% existing DCNN, and 85% RL-QNN for the NCRCRD dataset; for the SDBSDataset, the proposed technique achieved 89% prediction accuracy, 74% existing DCNN, and 79% RL-QNN; for the SHRUGDataset, the proposed technique achieved 97% prediction accuracy, 78% existing DCNN, and 89% RL-QNN.

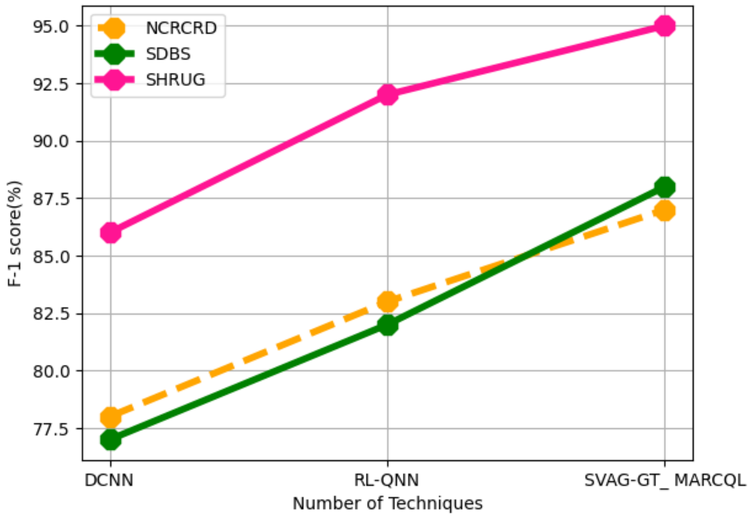

Figure-4 comparison of F-1 score

Figure 4 shows analysis in F-1 score. Here proposed technique attained F-1 score of 87%, existing DCNNattained 78%, RL-QNN 83% for NCRCRD dataset; for SDBSDataset proposed technique F-1 score of 88%, existing DCNNattained 77%, RL-QNN 82%; proposed technique F-1 score of 95%, existing DCNNattained 86%, RL-QNN 92% for SHRUGDataset.

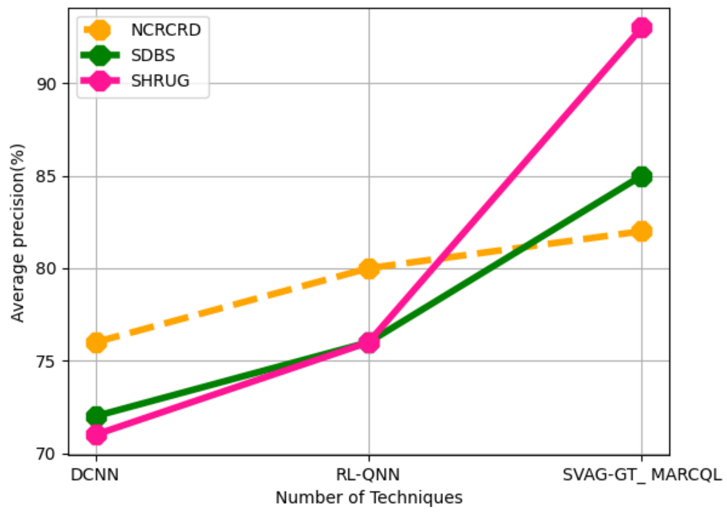

Figure-5 comparison of Average Precision

Analysis in Average Precision is shown in Figure 5. In the NCRCRD dataset, proposed technique obtained Average Precision of 82%, the existing DCNN attained 76%, and RL-QNN attained 80%; in the SDBS dataset, proposed technique obtained Average Precision of 85%, the existing DCNN attained 72%, and RL-QNN attained 76%; in the SHRUG dataset, proposed technique obtained Average Precision of 93%, the existing DCNN attained 71%, and RL-QNN attained 76%.

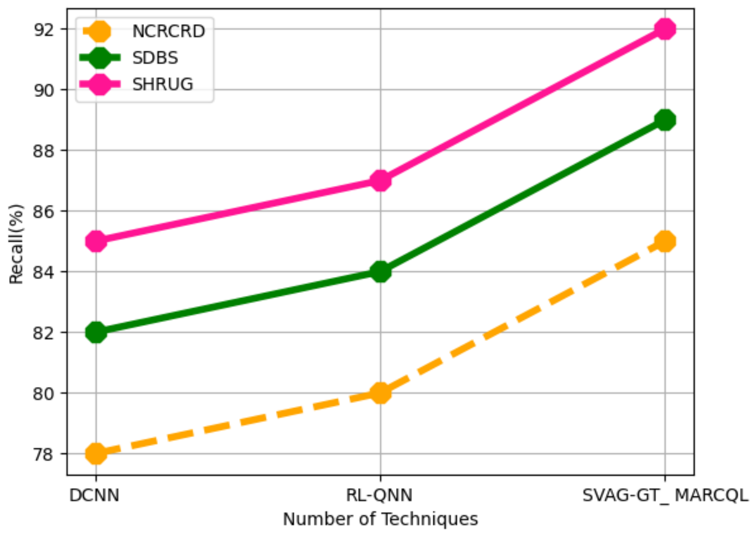

Figure-6 comparison of Recall

The recall analysis is displayed in Figure 6. Here, proposed technique achieved 85% recall, 78% existing DCNN, and 80% RL-QNN for the NCRCRD dataset; for the SDBS Dataset, the proposed technique achieved 89% recall, 82% existing DCNN, and 84% RL-QNN; for the SHRUG Dataset, the proposed technique achieved 92% recall, 85% existing DCNN, and 87% RL-QNN.

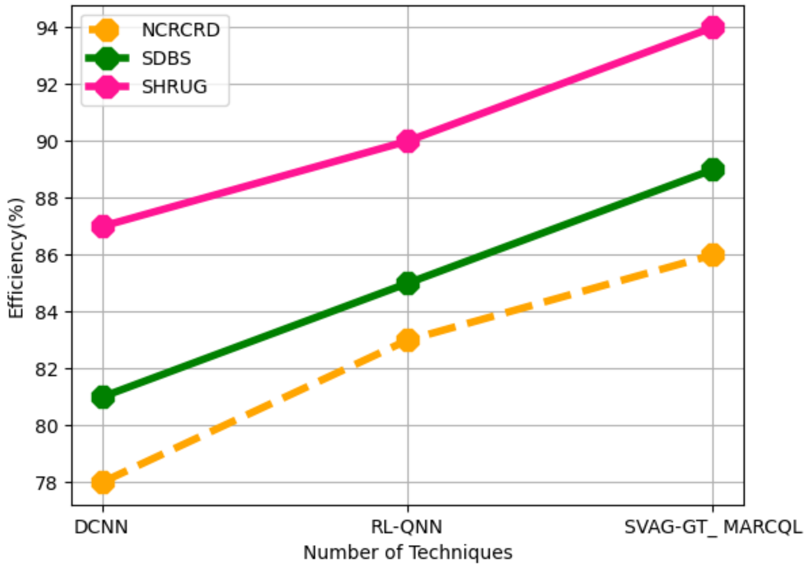

Figure-7 comparison of Efficiency

Figure 7 shows analysis in efficiency. Here proposed technique efficiency 86%, existing DCNN 78%, RL-QNN 83% for NCRCRD dataset; for SDBS Dataset proposed technique efficiency of 89%, existing DCNN 81%, RL-QNN 85%; proposed technique efficiency 94%, existing DCNN 87%, RL-QNN 90% for SHRUG Dataset.

Table 2 Percentage per company for each factor

	N	**Mean**	**Standard deviation**	**Percentile 25**	**Percentile 75**
Efficiency	122	4.10	4.87	0.00	5.59
Useful	122	8.19	11.26	2.27	10.71
Complementarity	122	0.30	0.79	0.00	0.16
Novelty	122	16.94	13.99	9.34	20.00
Performance	122	5.43	6.21	0.00	8.19
Transparency	122	1.82	5.06	0.00	1.14
Explainability	122	0.34	1.24	0.00	0.00
Effort	122	3.94	9.50	0.00	4.52

A significance level of 5% ($\alpha = 0.05$) was employed in the experiments. p value indicates probability that outcomes are the result of chance, assuming no differences exist between the groups. There is more evidence against the null hypothesis the lower the p value, which indicates that results are less likely to be the result of chance. An association is considered statistically significant if p-value is less than 0.05. Conversely, a p-value of 0.05 or above indicates absence of an association. The following is display of test name (A), statistic (Z), degrees of freedom (df), and p value: p-value, A(Z, df). The possibility of financing more than one million USD (p) is compared to likelihood of financing less than one million USD (1 - p) using the odds ratio (OR). Over this time period, the median number of tweets per company was 86.5, and the average was 252.12. The number of tweets by size did not change significantly: K-W (4.032, 2), p = 0.133. There were just two firms in the final group. The amount of tweets associated with each component was totaled for each company in order to ascertain which variables companies focused. Number of tweets relative to the total number of tweets from the company was determined for each factor (Table 2).

Confirmatory factor analysis results for the variables under study. $\chi2$ Df CFI TLI SRMR RMSEA RMR Zero-modeling 199.99 89/07/06/91/88/06 Model with six factors 89 0.07 0.05 0.92 0.90 0.05 200.00 Five-factor model 229.96 94 0.90 0.87 0.06 0.08 0.06 Four-component model 212.19 98 0.91 0.89 0.06 0.07 0.06 three-factor modelling 101 0.08 0.06 0.89 0.87 0.06 237.92 Two-component model 0.89 0.87 0.06 243.86 0.3 0.08 0.06 Single-factor model f n = 242 and 257.03 104 0.08 0.06 0.88 0.86 0.06. There is no relationship between any of the measures in the null model. Potential characteristics that were discovered were diversity of knowledge and strategic sensitivity. A possible component was identified by combining three subdimensions of entrepreneurial cognition. dA potential factor was identified by combining three subdimensions of knowledge diversity and entrepreneurial cognition. Together, the three subdimensions of knowledge variety, strategic sensitivity, and entrepreneurial cognition constitute a potential factor. Every measurement was added together to create a potential factor. The impact of six control variables in this paper on BMI and strategic sensitivity is represented by models 1 and 3. Model 2 supports Hypotheses 2a–2c. Model 4 provides evidence in favour of Hypotheses 1a–1c, demonstrating the significant beneficial impacts on BMI of entrepreneurship configuration. Model 5 demonstrates that strategic sensitivity significantly raises BMI ($\beta = 0.70$, $p < 0.01$), which is consistent with Hypothesis 3. Model 6 demonstrates that when strategic sensitivity and entrepreneurial cognition This demonstrates that, in addition to supporting Hypothesis 4 (4a–4c), strategic sensitivity may have a partially mediating effect. Regarding Hypothesis 5, OLS regression method is utilised to test as well as create the moderating effect of Knd, whilst ensuring strategic sensitivity and standardising Knd. According to study, interacting words significantly improve BMI, which lends credence to Hypothesis 5.

5. Conclusion

This study proposes a unique technique for cooperative tactics based on rural small company entrepreneurship that combines game theory with a machine learning model for conflict optimisation. The small business entrepreneurship approach is analysed using the support vector adversarial gradient game theory model. The optimisation was subsequently performed using multi-agent regression with convolutional Q-learning. Study contributes to the current literature on creditworthiness assessment by using a combination of variables and numerous forecasting approaches in the Baltic market. Evaluated method should make it easier for decision makers to assess SME creditworthiness by emphasising the importance of temporal considerations and suitable forecasting model selection, resulting in a beneficial impact on lenders' bottom lines through lower total capital requirements. SME companies should have easier access to financing if major lenders have a lower relative cost of capital. The data point to a tighter link between efficiency as well as value capture. In contrast, contemporary research on business strategy reveals that originality is primary driver of corporate performance. By identifying critical indicators that predict company birth and firm abandonment, we were able to acquire useful insights into the startup activities that lead to firm emergence. Achieving revenue, as well as the rate, timing, and focus of activity, are critical factors in forecasting venture gestation outcomes. Although these models can provide some direction, business frequently needs intuitive decision making, and heuristics help entrepreneurs function well in certain situations. Similarly, with their sector experience and sensitivity to entrepreneurial personality, professionals such as business angels or venture capitalists can offer sound counsel. Second, company emergence is a complex process in which additional circumstances may have a important impact on venture's outcome.

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This work was supported by the humanities and social sciences project of "Training Plan for 1,000 Young and Middle-aged Key Teachers in Guangxi Colleges and Universities", "Research on Rural Entrepreneurship under the Background of Rural Revitalization: Intergenerational Conflict, Resource Integration and Breakthrough Path" (project number: 2022QGRW066) ".

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