Determinants and Prediction of Farmers' Adoption Choice of Climate-Smart Agriculture Technologies in Shrimp Farming: Application of Machine Learning Based Algorithms

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Abstract

Shrimp is Bangladesh's second-largest source of foreign currency revenues, known as the country's "white gold." Bangladeshi shrimp farmers are new to climate-smart technology. The goal of this study is to fill in the gaps by looking into what makes people in Bangladesh accept climate-smart technologies (CSTs), focussing on factors affecting CSTs adoption for shrimp productivity, and predicting CSTs adoption using five machine learning (ML) algorithms. The research included 225 shrimp-farming families selected by using simple random sampling from two upazillas, namely Bagerhat Sadar and Shyamnagar, respectively, in Bagerhat and Satkhira districts in Bangladesh, renowned for their shrimp farming. This study applied five well-known Machine Learning algorithms, namely logistic regression (LR), random forest (RF), support vector machine (SVM), K-nearest neighbors (KNN), and Naïve Bayes (NB), to predict the adoption of CSTs in shrimp farming production. Based on the findings, it was shown that the average number of family members involved in shrimp farming was 1.293, and 14 climate-smart technologies are available, where 88.89% of farmers use poly-culture shrimp farming, which is a popular practice for shrimp production. When the accuracy of the models was evaluated, it was found that RF performed better than other models, but LR provided the greatest forecast of adoption (0.818% accuracy), determined based on numerous performance parameters. The growing demand for CSA technology within a certain socio-economic group and geographic setting requires a strategic and suitable governmental response. Policymakers and the government should prioritize education, agricultural experience, insurance, and credit. With this outcome, Bangladesh may pursue green growth.

Keywords: Adoption, Bangladesh, Coastal aquaculture, Climate-smart technology, Machine Learning algorithms, Shrimp

JEL classifications: C120, C310, C530, O120, Q120

Introduction

Bangladesh is one of the countries at greatest risk from climate change. According to the Global Climate Risk Index (GCRI), it was ranked seventh among the most climate-change-vulnerable countries in the world (UNDP, 2022). The agriculture of Bangladesh is challenged by unpredictable rainfall, extreme temperatures, salinity, floods, drought, river erosion, and tropical storms. These situations would be worsened due to climate change. Because temperature, light, rainfall, and radiation are significant contributors to agricultural productivity, the sector is more prone to variability. Droughts, extreme heat, and heavy rain will be more common and intense, particularly in regions that are already vulnerable to flash floods, landslides, and drought. Such risks create fragmentation in ecosystems, the loss of wildlife, an erosion of forest resources, and an alteration in livelihood patterns for coastal residents. Also, climate change is one of the leading risks to shrimp aquaculture, global food supply, and community livelihoods (IPCC, 2014). Globally, rising temperatures (Lobell et al., 2012), changing rainfall patterns (Prasanna, 2014; Mall et al., 2006), and increasing frequency of extremes caused by severe floods and droughts (Brida & Owiyo, 2013; Singh et al., 2013) could pose a serious threat to agricultural production. In addition, there is a lower crop suitability, low biodiversity, low input use efficiency, and large insect diseases (Zabel etal, 2014; Norton, 2014). Agriculture must change to continue protecting food and livelihoods. Many strategies are available for mitigating climate risks in shrimp production. Climate-smart agriculture (CSA) technologies, practices and services focus on increasing productivity, enhancing resilience and reducing greenhouse gas emissions at the same time (FAO, 2010). Climate-Smart Agriculture (CSA) aims to deliver diverse forms and functions of resilience that maintain food and income security under climate change scenarios (Vermeulen et al., 2012; Lipper et al.). Agroecological practices and technologies, information services, and new communication channels adapted to local descriptions are thus combined in CSA options (CIAT 2014). For the purposes of this study, we define a technology or practice as climate-smart if it contributes to at least one of the CSA goals: higher productivity, greater resilience, and/or lower emissions. Farmers must invest in these options, but they must do so in the face of climate risk that also encompasses both short and long-term nature.

A meta-analysis, compared with non-adoption, identified that the application of these practices increases yields by 7–15% (standard deviation: ±8%) on average (Challinor et al., 2014). Adaptation, however, comes with dangers depending on temperature and rainfall shifts (Easterling et al., 2007). CSA technology studies responding to local problems also showed potential increases in yields, more efficient use of inputs, net income raising, or reducing emissions. (Khatri-Chhetri et al., 2016; Sapkota et al., 2014; Gathala et al., 2011) Bangladesh must be one of the most densely populated and agriculturally intensive countries, with around 9.1 million hectares (i.e., 70% of land area) devoted to feed more than 170 million people, including above 15 million farming households, during 2018–2019 (BBS, 2020). The economics of shrimp culture are critical, as it provides foreign exchange and increases food production; the industry will also diversify the economy and generate jobs. The shrimp is referred to as Bangladesh's "white gold" as it accounts for about 56.76 percent of overall fish production (DoF, 2019) and constitutes the second-largest foreign currency-earning source with an export rate of up to 97%. Including wild catch, total production of shrimp increased from 1.60 lakh MT in 2002–03 to 2.58 lakh MT in 2018–19 with a CAGR growth rate of 1.44% (DoF, 2019).

Over the past 18 years, there has been a rapid expansion of coastal aquaculture, such as shrimp and finfish farming. The legal framework for incorporating climate-smart technologies (CSTs) into development policies is extremely important, as the use of these technologies is widely regarded in literature as a fundamental way to adapt agriculture and fisheries towards climate change. Policymakers, scientists, and farmers, however, are still very new to the CSA concept 22. Farmers have a wide array of alternative technologies that could be adopted alone, and/or in conjunction with each other to adapt to the different climatic scenarios (Dorfman, 1996; Teklewold et al., 2017). Introduction 1.2 The impact of farm level on farmers' preferences for technologies at national and global levels. However, variations in culture, knowledge of new technologies, access to resources, aspirations, and socio-economic status impact upon farmers' likelihood to adopt innovative agricultural practices (Maguza-Tembo et al, 2017). Farmers may further adapt CSTs, or they may incorporate them with other practices according to local need. Shrimp farming: There is mounting concern that it is not ecologically sustainable in the long term. The government has been implementing different policies, programs, and action plans to counter the effects of climate change. In addition, highly used coastal resources for the last few decades without sustainability consideration, and very low productivity in shrimp were observed.

What influences farmers to adopt different CSTs needs further attention from scientists and policymakers. The identification and validation of climate sensitivities (CSTs), as well as their tradeoffs, establishes a foundation for planning by identifying priority investments to increase resilience in shrimp production across countries. This means that, in planning farm-level strategies, consideration can be given only to those options that have been screened and ranked by local farmers based on climate risks relevant at the farm level (FAO, 2012). Modern programs, however, often have no knowledge of this. A need for more effective policy and action: Using evidence on farmers' priorities to inform stakeholders about their collective interests in relation to government policies and institutions. Changes in aquaculture methods, community attitudes, and even farm location are needed to adapt to climate change and mitigate its effects. Aquaculture and, hence, shrimp farming, with resilience, adaptability, and species diversification, can respond to climate change and provide alternative livelihoods (De Silva & Soto, 2009). Production is likely to increase with simple technologies available for easy adoption by farmers, touching both low-cost and high-value species. (Troell, 2009) While the advantages of CSA technologies are well recognized, adoption rates in shrimp farming remain dire. Adoption of new technologies by farmers is sensitive to various factors, including socio-economic characteristics of the household, local environmental conditions, and features of the new technology (Campbell et al., 2012; Below et al., 2012; Deressa et al., 2011). A significant challenge to scaling up CSA across regions is understanding how to identify, prioritize, and disseminate climate-smart agriculture (CSA) technologies that are appropriate for local climate risks and needs. A grasp of how much climate change technologies matters and the factors mediating their adoption is key to effective climate policy as well as sustainable shrimp production. But these things are not adequately researched in Bangladesh. Only limited research has been done on shrimp farming and climate change, e.g., climate-smart agriculture technologies (CSATs) for rice production in Sarker et al. (2022). Their study revealed that factors such as education, farming experience, eating from their own fruits and vegetables, family size, and access to means of production were important for rice cultivation. In Bangladesh, Mahashin and Roy investigated climate-smart agriculture practices, noting that farmers use CSA on a micro scale, but promoting innovative ideas, as well as taking investment in knowledge, along with capacity building, can be the solution towards widespread adoption. The analyses indicate that different practices and technologies respond to three global

challenges: food security, climate change impacts on agriculture, and agriculture's effects on climate change. Although the existing literature discusses the adoption of CST widely, mechanisms that determine climate-resilient practices in agriculture, including shrimp production, have received limited attention. The new challenge for shrimp farmers is to develop adaptability and resilience to climate disruptions. This challenge can only be met through investment in protective infrastructure and climate-proof production technologies (Kais & Islam, 2021). ML methods have shown good results in the field of prediction tasks, even exceeding traditional statistical models. Machine Learning (ML) is already ubiquitous in social science and agricultural research. In this line, a lot of researchers are leveraging different kinds of ML algorithms, including random forest (RF), support vector machines (SVMs), and even convolutional neural networks to predict technology adoption. In this study, five widely known ML algorithms, namely, LR, RF, SVM, K-nearest neighbors (KNN), and NB, are compared in terms of prediction performance for climate-smart technology adoption in Bangladesh. It is critical to estimate the uptake of these technologies by farmers properly to improve their livelihoods. This involved machine learning features that identify patterns in data from various areas, including social sciences, agriculture, and medicine, to develop predictive models. Only a few studies have attempted to use machine learning (ML) for predicting the adoption of climate-smart technologies. With this study, we seek to enhance climate-smart and sustainable shrimp production in the coastal belt of Bangladesh through improved shrimp productivity at a fraction of costs and into policy recommendations while predicting CST adoption using multiple ML algorithms. So far as we are aware, this is the first study to forecast the adoption of climate change smart technology in shrimp farming in Bangladesh. The research highlighted will make an important contribution to the field of literature to increase shrimp productivity.

Theoretical Framework

In this paper, we build on the expected maximum utility theory (Schoemaker, 1982) and the diffusion of innovation theory (Rogers, 2003). The theory of expected utility maximization implies that farmers choose climate-smart agriculture (CSA) technology if they realize more expected benefits from this CSA practice rather than other traditional methods or by continuing with the usual farming method without any technology change. This theory supports the diffusion of innovation theory by providing insights into how and why farmers choose to accept

or reject these practices. CSA is critical for economic development and a growing need as climate change becomes a more serious issue. The diffusion of innovation theory is concerned with how the diffusion of innovations is communicated through certain channels amongst members of a social system and can be divided into adopter categories and modes: this means how an innovation is successfully brought before and adopted into practice (Rogers, 2003). According to Rogers, in this study, household factors (gender, age, education, household size, farm size, and income) are like the characteristics of innovators. The CSA practices are the innovation, whereas institutional factors (access to information, extension services, credit, training, and farmer associations) serve as communication channels. Data availability and technology awareness (Kabunga et al., 2012; FAO, 2013) are prerequisites for farmers to adopt CSA. Adoption is a social-cultural-technical process that relies on resources (labor, money, and social networks) (FAO, 2013). When these resources are organized and allocated properly, they assist farmers in adopting and diffusing newer practices that enhance productivity, as well as being instrumental in climate change adaptation (Mutoko et al., 2014; Sarker et al., 2022). Encouraging collaboration partnering with other organizations could also accelerate the adoption of CSA practices (Odongo, 2010).

The basic framework of this climate-smart agriculture (CSA) technology adoption concept applied to shrimp farming can be simply summarized using some key factors needed for growth, productivity, resilience, and sustainability. Core objectives include increasing yields, climate risk adaptation, and minimizing environmental impacts. This framework illustrates that the farmers' adaptive capacity (determined by their socioeconomic status and the level of support from existing institutions) plays a significant role in CSA adoption (see Figure 1). Socioeconomic characteristics: farm size, education level, number of people involved in shrimp farming activity, experience, and household income. Institutional support also accounts for a large share of agricultural productivity that involves access to information, credit, extension services, training, and farmer associations. So, CSA can help provide shrimp farmers with solutions to problems like salinity of water or changes in the climate, considering sustainability, adaptation to changing conditions, and reduction of greenhouse emissions. The adoption process depends on farmers' risk perceptions, as well as perceived benefits and challenges, which ultimately impact economic, environmental, and social outcomes. Achieving long-term sustainability in shrimp aquaculture requires cooperation among stakeholders, financial backing, and strong policies.

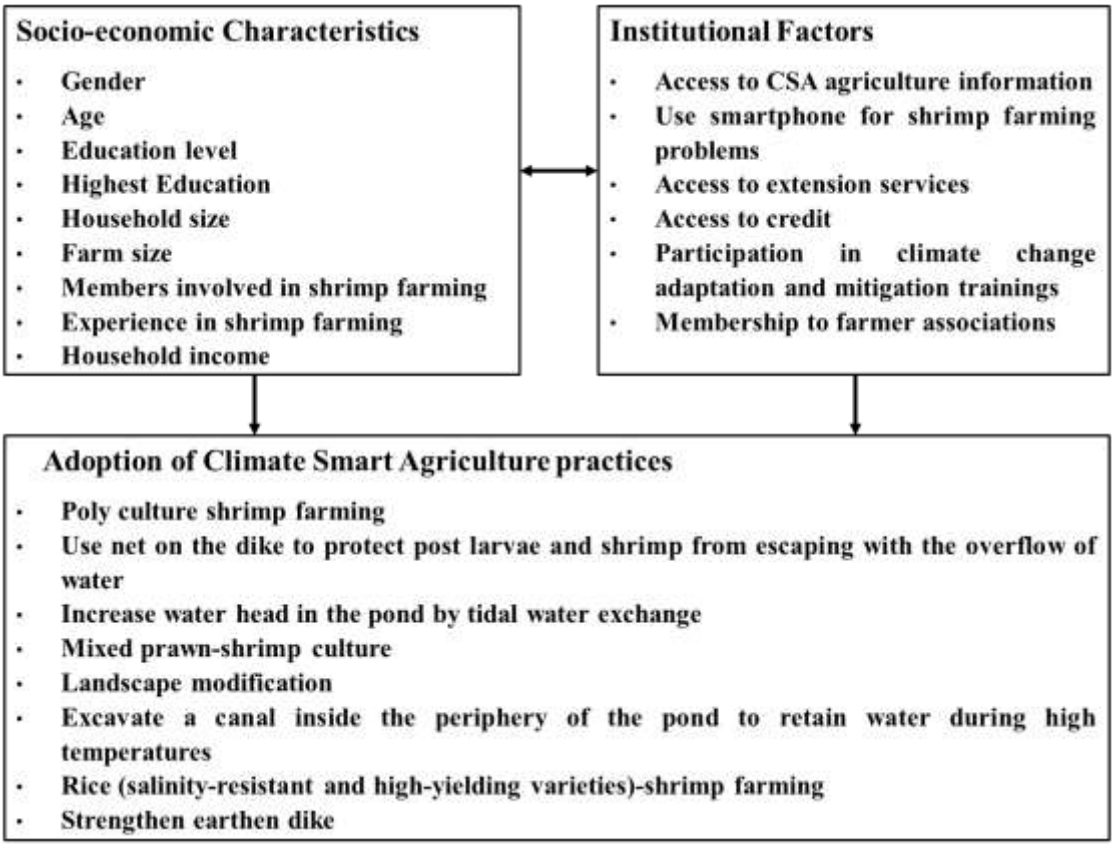


Figure 1: The conceptual framework of Climate Smart Agriculture (CSA) Technology Adoption in Shrimp Farming

Methodology

Study locations

The main study was an assessment of coastal ecosystems with heavy shrimp farming. The regions selected for study had a history of high shrimp production, namely the Bagerhat and Satkhira districts in Bangladesh. The two districts are together by far the largest shrimp-producing districts out of sixty-four. Both have thriving sectors for commercial and intensive shrimp farming. These areas represent the main shrimp-producing region of the country. With shrimp as the most common household staple, and rice as the main crop. Two upazilas were selected for the study, depending on shrimp farming intensity: Bagerhat Sadar in Bagerhat and Shyamnagar in Satkhira (Figure 2).



Figure 2: Sample collection based on two upazillas in Bagerhat and Satkhira districts

Sampling design

Shrimp producers were selected by a three-stage sampling process. First, two districts were chosen. Furthermore, two upazillas from each district were chosen for inclusion based on their relevance. We surveyed these shrimp farmers to gather data at the upazilla level, where shrimp farming exists. Lastly, we used simple random sampling to select farmers of each upazilla under the climate-smart technology experiment.

Sample size and technique

Methods: A simple random sampling method was utilized to recruit participants, and data were collected through a questionnaire. One hundred shrimp farmers from Bagerhat district and 125 from Satkhira district were selected randomly. A total of 225 farmers from these two upazilas were surveyed. We prioritized the study objectives above all else at every step of respondent selection.

Preparation of the questionnaire and collection of data

A semi-structured questionnaire was employed to conduct interviews among the households. Enumerators conducted face-to-face interviews after training by the principal investigator (PI). The PI provided supervision of the interviewer, while the lead researcher also assisted in

carrying out interviews. Design and validation of the final questionnaire. Based on the results obtained in a pre-test survey, through a pilot questionnaire, the final version was developed. Pretest: understanding how people respond to our questions is a crucial step in survey development, and hence, pre-testing them. This also indicates what respondents can do or provide the required information. Although pre-tests provide a direct indication of the validity of most questionnaire items. Qualitative and quantitative data were collected based on the variable types and respondents. Data was collected from two sources: primary and secondary. We formulated our main data collection through interviews with selected respondents. The data was edited and analyzed once it had been collected.

Dependent variable

The farmers' adoption status of shrimp is the dependent variable in this study. In the study area, farmers adopt 14 different climate-smart technologies. We surveyed 225 shrimp producers about the technologies they utilize. We calculated the total number of climate-smart technologies and divided it by the number of farmers, averaged across farmers. When a farmer's total was below average, we assigned them 0 for adoption. We labeled it 1 if it was above the mean.

Independent variables

We chose a set of independent variables from socioeconomic and demographic characteristics that are related to their adoption of climate-smart technologies for shrimp farming. These are: age (years), sex (male, female), education level (years), highest education level in the family, years of shrimp farming experience, total number of family members (male, female, children), annual expenditure (Taka), farm size (Decimal) smartphone use or not, internet usage (Yes, No) and availability of phones to ask for help regarding any issue related to shrimp farming and if there are any social networking groups based on shrimp farming to join or not; Credit for shrimp farms available or not; if received any community support as a farmer.

Ethical consideration

Ethical discussions for the current study were carried out according to the regulations of the Research Ethics Committee, Department of Agricultural Statistics, Sher-e-Bangla Agricultural

University, Dhaka-1207. Participants are informed of the purpose of the study, their identity remains anonymous, and everyone provides consent.

Analytical techniques

The data is analyzed using both descriptive and advanced statistical methods.

Descriptive analysis

Respondents' profiles can be determined using tabular and graphical analysis. The tabular method helps to calculate the socio-economic features of adopters of climate-smart technologies. This method is simple, common, and easy to digest. What it does is offer simple metrics, such as averages, percentages, and ratios. A chi-square test is then performed to compare the socio-demographic and economic characteristics between the two geographical regions. This is a (5 %) level of significance test.

Advanced statistical analysis

The study uses an advanced statistical model, specifically a logistic model, to achieve its objectives.

Model specification for identifying the determinants

It analyzes what affects farmers using a multinomial model when they adopt climate-smart technologies (CSTs). Climate-smart programs that are designed and implemented by pointing out what drives farmers to invest in technologies. These adversities can be socio-economic, but they can also relate to climate. We use a discrete dependent variable with multiple categories to represent CST adoption in this research. Moreover, despite the discrete nature of the outcome, multinomial logit models do not incorporate the order of the dependent variable (Beggs et al., 1981; Hausman & Ruud, 1986).

$$\sum_{j=1}^{j} P_n(j) = F(\alpha_j - \beta_j X_n, \theta),\ j = 1,2.....J-1$$

$$P_n(J) = 1 - \sum_{j=1}^{J-1} P_n(j)$$

where $P_n(j)$ is the probability that farmer n (n = 1, ……, N) chooses climate smart technology j, α_j is an unknown parameter to be estimated with β_j, X_n is a vector of characteristics specific to farmers and location, β_j is a vector of coefficients, and the shape of the probability distribution function, F, is determined by the θ parameter. We assume that the error term over observations follows a normal distribution, which means its mean and variance are equal to 0 and 1, respectively. This function will allow us to easily use D logits to estimate a log-likelihood and its derivatives. It has been applied to examine the determinants of climate change adoption decisions across locations (Balew et al, 2014; Gbetibouo, 2009). The dependent variable in our analysis represents the choice that a farmer would make among several technologies to select climate-smart technology. These explanatory variables include household characteristics such as age and the highest level of education in the household, experience, landholding, family size, household spending, use of smartphone used for shrimp farming (dummy), SNS (dummy), and access to credit (dummy). These variables were selected based on data availability and prior studies.

Chi-square test to identify the relationship

The relationship between explanatory variables and adoption status was tested in a bivariate setting. In the bivariate setting, we applied for the Chi-square independence test. Mathematically, the Chi-square statistic can be defined as follows:

$\chi^2 = \sum$ (observed frequency$_i$ –Expected frequency$_i$)/ Expected frequency$_i$, i=l,…,n

Statistics follow the Chi-square distribution with the degrees of freedom ([number of rows – 1] × [number of columns – 1]).

The main advantage of the model is that it allows the analysis of the potential correlation between unobserved disturbances (error terms) and the correlation between the adoption of each CSA practice (Mittal & Mehar, 2016; Mussida & Zanin, 2020; Sarker et. al., 2022). The analysis was based on the expected utility maximization of adoption of a specific CSA practice by a farmer if the expected utility from adoption (U_{ij}^*) was greater than the expected utility from any other alternative practice, including farming as usual (i.e., not adopting any climate-smart agriculture practice) (U_{ij}),

$$Y_{ji}{}^{*} = U_{ij}{}^{*} - U_{ij} > 0$$

Where Yji is the net benefit (latent variable) the farmer receives from adopting jth climate-smart agriculture practices.

Consequently, the model assumed that each binary observed variable takes a value 1 if, and only if, the continuous latent variable is greater than zero:

$$Y_{ji}{}^{*} = X_{ji}\beta_{ji} + \varepsilon_{ji}$$

Where Y_{ji}^{*} is a latent variable that captures the unobserved preferences associated with the choice of three CSA practices and is influenced by observed characteristics (Xji) and unobserved characteristics captured by the stochastic error term (ε_{ji}). Using the indicator function, the unobserved preferences in the equation are translated into the observed binary outcome equation for each choice as follows:

$$Yji = \begin{cases} 1 \\ 0 \end{cases} \quad if\ Y_{ji}{}^{*} > 0$$

In a binary model, where the choice to adopt several CSA practices in response to climate change is possible, the error terms jointly follow a Normal Distribution with zero conditional mean and variance normalized to unity (for identification of the parameters).

Following the form used by Hemmert et al. (2018), the log-likelihood function associated with a sample outcome is then given by:

$$lnL = \sum_{i=1}^{N} \omega_i \ ln\ \Phi\ (\mu_i\ ,\Omega)$$

Where ω_i is an optional weight for observation i, and Φ is the standard normal distribution with arguments μ_i and Ω , where μ_i can be denoted as:

$$\mu = (k_{i1}\ \beta_1 X_{i1,}\ k_{i2}\ \beta_2 X_{i2,}\ k_{i3}\ \beta_3\ X_{i3}\ ),\ \text{while}\ \Omega_{jk}=1\ \text{for}\ \ j=k$$

And

$$\Omega_{jk} = \Omega_{kj} = k_{ij}\ k_{ik}\ p_{jk}\ \text{for}\ j \neq k,\ k=1,2,3\ldots\ \text{with}\ k_{ik}= 2y_{ik}-1$$

Machine learning algorithms

We used the following five different supervised algorithms to predict the adoption status of climate-smart technologies in shrimp farming (Figure 3).

Logistic regression

LR was a "statistical learning" technique, which is a "supervised" ML method specifically used for "classification" tasks. It uses the maximum likelihood estimation procedure to estimate the parameters of interest. Let X_{i1}, X_{i2} … X_{ip} be a set of explanatory variables, which can be quantitative variables or index variables that refer to the level of categorical variables, and Y is a binary variable, which has a Bernoulli distribution of a parameter πi, then the logit regression model is,

$\log[\frac{\pi i}{1-\pi i}] = \beta_o + \beta_1 X_{i1} + \ldots.. + \beta_p X_{ip}$; β_i be the parameters.

Random forest

RF is a classification method that uses ensemble learning. It builds many decision trees during training, and the result combines the outcomes from each tree (Zhang et al., 2015).

Support vector machine

SVM is a widely used classification algorithm and is effective at handling nonlinear data. Chen Junli and Jiao Licheng clearly explained SVM's classification strategy (Junli et al., 2000).

K-nearest neighbors

KNN is one of the simplest and most widely used classification algorithms. It can handle multiclass label classification problems and has good generalization ability (Güvenç et al., 2021). The algorithm stores each available case and classifies new cases by measuring their similarity to stored cases.

Naive Bayes

NB classifier is based on Bayes theory, a probabilistic model that assumes strong independence among the features. Due to its ease of construction, it does not require estimating complex parameters, making it especially useful in the treatment field. Although basic, NB classifiers are

still widely used because they can compete with more complex classification methods (Vembandasamy et al., 2015).

Applied approach

We started by pre-processing: finding the missing values. We then used 75% of the samples in each group as the machine learning algorithm training data set and held another 25% to form a test data set for validation. We employed 10-fold cross-validation for model training. K-fold cross-validation was done on the training set, while model performance evaluation was made in the test set.

Model evaluation

Six evaluation metrics were considered: accuracy, sensitivity, specificity, PPV, NPV, and Cohen's kappa. Descriptive statistics were performed on all data using SPSS version 25 (IBM Corporation, Armonk, New York NY, USA) and R version 4.3.1 (R Core Team).

Accuracy. Accuracy is one of the ways to see how well predictive models perform. It indicates the number of right predictions divided by the total number of tested data points. This can be calculated on the following basis:

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$$

Sensitivity. Sensitivity indicates how well our model is at predicting positive class events. This is also called recall. Mathematically, we can express the sensitivity as:

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Specificity. Specificity measures the ability of a test to correctly identify negatives. It also corresponds to the rate of false positives. Here is the formula for calculating specificity:

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive}$$

Positive predictive value. To know how often a positive prediction is correct, we use the positive predictive value. It indicates the ratio of true positive results to false positives among all positive results. The positive predictive value can be calculated as:

$$Positive\ predictive\ value = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Negative predictive value. Negative predictive value is the proportion of all negative tests that are true negatives (as compared to false negatives). A true negative is when a negative prediction aligns with a negative outcome. This is sometimes called specificity. False negative: a negative prediction is made, but the result is positive. This is called a Type II error as well. Negative predictive value is defined as:

$$Negative\ predictive\ value = \frac{True\ Negative}{True\ Negative + False\ Negative}$$

Cohen's Kappa. Cohen's Kappa (κ) calculates how well the predicted class made by our model matches the actual classification in a data set. Cohen's kappa was interpreted with the guidelines published by Landis and Koch: Below 0 means no agreement; 0 to 0.20 means slight agreement; 0.21 to 0.40 means fair, from 0.41 to 0.60 means moderate, from 061 to.080 substantial, and from.81-1 almost perfect agreement.

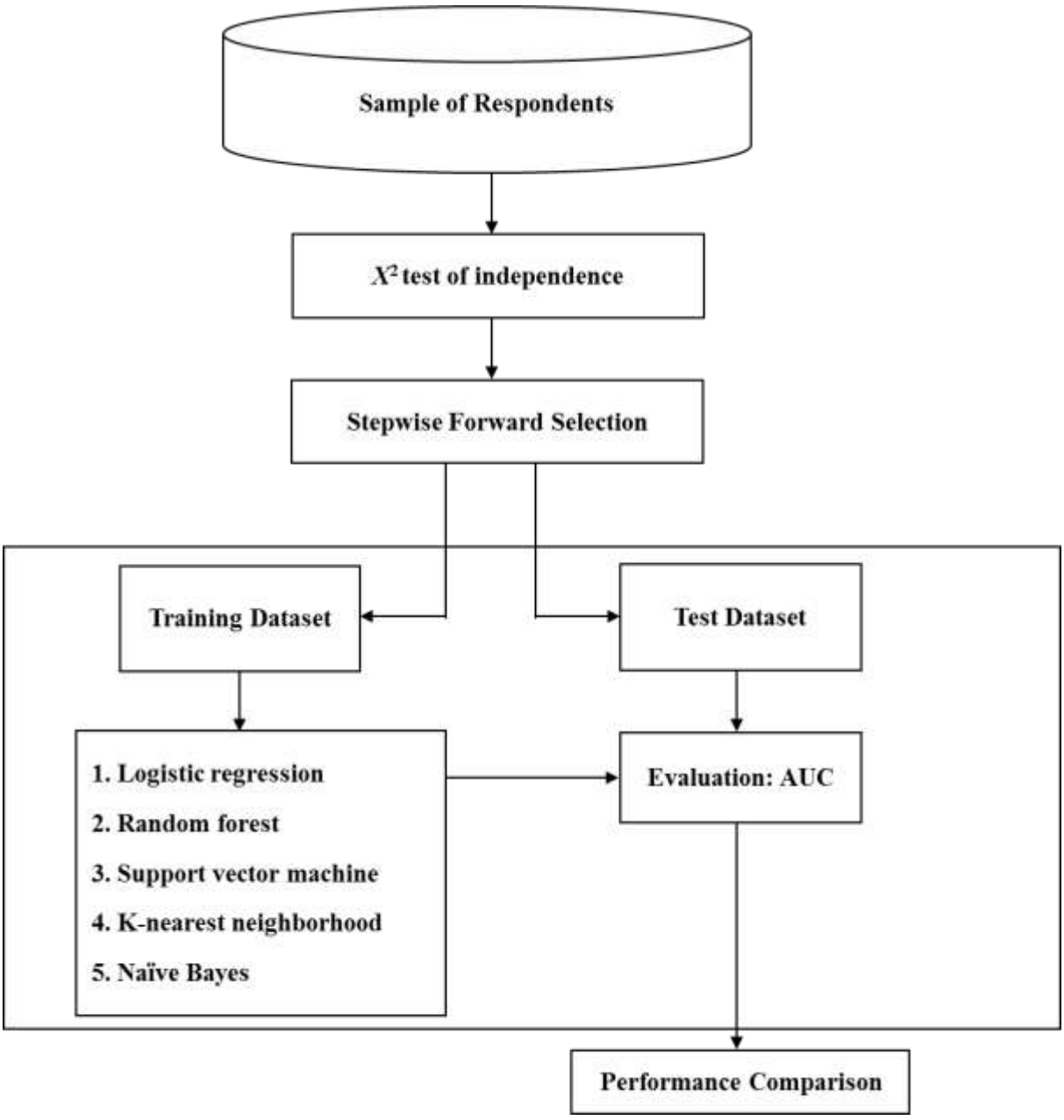


Figure 3: Model selection procedure

Results and Discussion

Descriptive statistics of the variables

Table 1 displays descriptive statistics of some basic characteristics of the households of shrimp farmers in Sathkhira and Bagerhat districts. It provides the minimum, maximum, mean, and standard deviation for the households of shrimp producers in Sathkhira and Bagerhat districts. The average respondent's age and highest education in the family are 42.29 ±12.58 years and

12.95 ±3.97, respectively. Higher levels of education are thought to be linked to increased productivity and access to knowledge about new and better technology (Sarker et al., 2022; Deressa, 2009). The respondents' shrimp cultivation experience is 14.59±10.06 years, and their annual family income is 335.84±346.88 thousand TK. The respondent's annual household average total expense is 223.44 ±196.04 thousand Tk.

Table 1: Descriptive statistics of characteristics of shrimp producers in Satkhira and Bagerhat Districts

Variables	Minimum	Maximum	Mean	Std. Dev.
Age(years)	19.0	86.0	42.29	12.58
Education(years)	1.0	17.0	9.42	4.60
Highest Education (year)	1.0	17.0	12.95	3.97
Total family members	2	20.0	5.10	2.12
Members involved in shrimp farming	0	10.0	1.29	0.82
Experience in shrimp farming (year)	0	40.0	14.59	10.06
Total landholding (decimal)	6	2112.0	269.42	328.74
Annual household income (thousand tk)	20	2660	335.84	346.88
Annual Expenditure (thousand tk)	12	2450.0	223.44	196.04

Relationship with a person who is the most reliable for you when you want to obtain farming knowledge

Figure 4 refers to the individual's knowledge and experience in shrimp aquaculture. Many farmers rely on their family or relatives for agricultural knowledge, as indicated by the graph. Approximately 42.7% of farmers in Bagherhat and Satkhira rely on their family and relatives for information regarding shrimp cultivation. Approximately 12.4 percent of farmers receive information from friends. Only 2.2% of farmers collect/get information from extension officers. It is estimated that 9.3 percent of farmers obtain agricultural knowledge from input sellers, while approximately 5.3 percent of producers receive information from buyers.

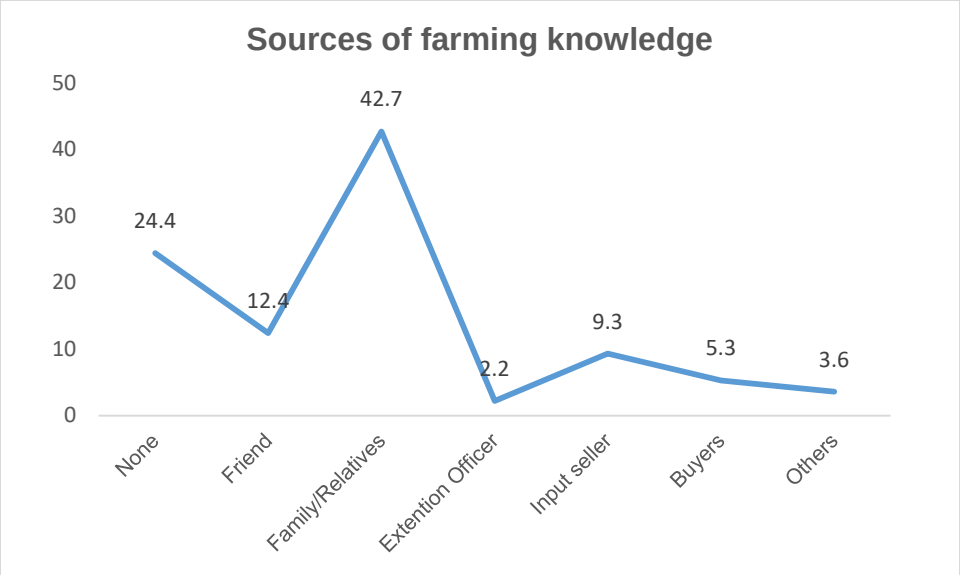


Figure 4: Sources of farming knowledge of shrimp farmers

Most preferred climate-smart technologies for shrimp production

During shrimp farming, different types of technology are used. The use of technology improves the efficiency, productivity, and sustainability of shrimp farming. Table 2 demonstrates that poly culture shrimp farming technology is famous among farmers in both areas of Satkhira and Bagherhat. About 88.89% of the farmers from Satkhira and Bagherhat use polyculture shrimp farming. From Table 2, we see that about 72.44% of the farmers use a net on the dike, which protects the post larvae and shrimp from escaping with overflow of water. The farmers in the study area use the tidal water exchange, which increases the water quality in the pond. It introduces new, good-quality water, which increases oxygen levels and reduces the chance of disease in the pond. About 63.11% of farmers from Satkhira and Bagherhat increase the water head in the pond by tidal water exchange. About 58.22% of the farmers from Satkhira and Bagherhat used mixed prawn-shrimp culture. Only 8.44% of the farmers in both areas provide shade by adopting aquatic plants. From Table 2, we see that about 12.44% of the farmers from Satkhira and Bagherhat maintain healthy and productive stocking density. The percentage of water aeration is very low in the study area, about 3.11% use this technology in their farming. Most farmers don’t follow an intensive monitoring system; only 4% of the total farmers from Satkhira and Bagherhat use this technology.

Table 2: Most preferred climate-smart technologies for shrimp production

Sl No.	Technologies	(Percentage)	Rank
1	Poly culture shrimp farming	88.89%	1st
2	Use net on the dike to protect post larvae and shrimp from escaping with the overflow of water	72.44%	2nd
3	Increase water head in the pond by tidal water exchange	63.11%	3rd
4	Mixed prawn-shrimp culture	58.22%	4th
5	Landscape modification	47.56%	5th
6	Excavate a canal inside the periphery of the pond to retain water during high temperatures	32.44%	6th
7	Rice (salinity-resistant and high-yielding varieties)-shrimp farming	24.89%	7th
8	Strengthen the earthen dike	23.56%	8th
9	Maintenance of healthy and productive stocking density	12.44%	9th
10	Increase the depth of water-by-water exchange or groundwater irrigation	12%	10th
11	Provide shade by adopting aquatic plants	8.44%	11th
12	Integrated mangrove-shrimp cultivation	4%	12th
13	Intensive monitoring	4%	12th
14	Aeration of water	3.11%	13th

Association between selected covariates and climate-smart technology adoption status of shrimp farmers

The climate-smart technology adaptation status with the background characteristics of the selected covariate is shown in Table 3. In terms of adoption choice of climate-smart agriculture (CSA) technologies, the percentage of male farmers was higher than female farmers, 99.1% of male farmers and only 0.1% of female farmers, 72% of the respondents were aged between 31 to

60 years, 87.1% of respondents were involved in shrimp farming as their main occupation, 45.8% of farmers used smartphone, 43.1% of respondents used internet on their phone, while only 10.7% of farmers used smartphone for help about shrimp farming related problems, only 1.3% of respondents participated in SNS groups for shrimp farming, 27.6% take credit for shrimp farming, while 4.9% get community support for farming, 0.4% respondents receive training for using CSA technologies and get technological assistance and only 0.9% respondents receive training on intensive farming. It was found that all these selected covariates were significantly related to the climate-smart agriculture technology adoption status.

Table 3: Assessing the association between selected covariates and the climate-smart technology adoption status of shrimp farmers using the chi-square test

Covariates	**Percentage (%)**	**p value**
Gender		
Male	99.1	0.154
Female	0.9	
Age (years)		
<30	21.30	
31-60	72.00	0.001
>60	6.70	
Main Occupation		
Shrimp farming	87.1	
Crop farming	4.9	
Business	3.6	
Service	4.0	0.000
Livestock	0.4	
Others		
Secondary Occupation		
Shrimp farming	12..9	
Crop farming	42.7	
Business	12.0	
Service	1.3	0.000
Livestock	1.8	
Others	9.3	
None	20.0	
Education		
1-5	33.8	0.000
6-10	32.4	
11-12	8.0	
13-17	25.8	
Highest education		
1-5	6.7	0.000

6-10	24.0	
11-12	15.1	
13-17	54.2	
Use Smartphone		
Yes	45.8	0.000
No	54.2	
Internet on phone		
Yes	43.1	0.000
No	56.9	
Use smartphone for shrimp farming problems		
Yes	10.7	0.029
No	89.3	
Electricity in house		
Yes	94.2	0.011
No	5.8	
Participate in SNS group		
Yes	1.3	0.080
No	98.7	
Take credit		
Yes	27.6	0.139
No	72.4	
Get community support		
Yes	4.9	0.362
No	95.1	
Source of fresh drinking water		
Yes	68.0	0.000
No	32.0	
Receive training on CSATs		
Yes	0.4	0.318
No	99.6	
Training on intensive farming		
Yes	0.9	0.157
No	99.1	
Get technological assistance		
Yes	0.4	0.318
No	99.6	

Determinants of the adoption of climate-smart technologies in shrimp farming

The logit model was applied to determine the adoption of climate-smart technologies in shrimp farming. Large producers are often more financially stable, which increases the potential and degree of CSA in production (Luu, 2020; Fadina et al., 2018). In this model, the explanatory variables were age, the highest level of education in the household, experience, landholding, family size, household expenditure, use of smartphone for shrimp farming (dummy), SNS

(dummy), and access to credit (dummy). The results of a logit equation on climate-smart technologies adoption status are presented in Table 4. The logit analysis showed that five variables, namely age, the highest level of education in the household, landholding, family size, and use of smartphone for farming (dummy), were statistically significant.

Table 4: Results of the estimated logit equation of climate-smart technologies adoption status (z statistics in parentheses)

Variables	Coefficients
Age	0.042**
	(2.616)
Highest Education of the household	0.234***
	4.719
Experience in shrimp farming	0.009
	(0.951)
Landholding	0.001**.
	(2.183)
Family size	-0.108*
	(1.655)
Household expenditure	0.001
	(0.641)
Use of smartphone for shrimp farming	0.434*
	(1.773)
SNS	1.530
	(0.521)
Access to credit	0.036
	(0.701)

***significance at 0.01 probability level, **significance at 0.05 probability level, **significance at 0.10 probability level.

Performance of machine learning algorithms

The positive effects on shrimp farming are consistent with previous findings on the effects of technology (Medarametla et al., 2023; Hasan et al., 2022; Das et al., 2022), but our study first to focus on predicting the climate-smart technology adoption in shrimp farming in Bangladesh. In this study, five different ML algorithms were used to classify the levels of climate-smart technology adoption in the test data set. The predictive performances of these algorithms are compared based on performance parameters such as accuracy, sensitivity, and specificity. In

addition, Cohen's k statistics were used to determine the discrimination accuracy of the algorithm. The performance indicators used to predict the climate-smart technologies in shrimp farming for each ML algorithm by testing data sets are shown in Table 5.

Table 5: Performance indicators of all five machine learning algorithms to predict the adoption status of the climate-smart agriculture technologies

	Algorithms				
	LR	**RF**	**SVM**	**KNN**	**NB**
Test set					
Accuracy (%)	0.808	0.838	0.626	0.704	0.653
K	0.64	0.75	0.40	0.55	0.39
Sensitivity (%)	0.718	0.827	0.907	0.800	0.938
Specificity (%)	0.687	0.776	0.139	0.634	0.125
PPV	0.697	0.798	0.436	0.615	0.517
NPV	0.709	0.843	0.670	0.812	0.666
Recall	0.75	0.90	0.55	0.70	0.95
f_1-score	0.79	0.88	0.65	0.76	0.68

LR: Logistic regression, RF: Random Forest, SVM: Support vector machine, KNN: K-nearest neighborhood, NB: Naïve Bayes, PPV: Positive predictive value, NPV: Negative predictive value, CI: Confidence interval

LR achieved 81.8% accuracy with a sensitivity of. Specificity: 68.7% and specifically 71.8%. The model achieved 83.8% accuracy, 82.7% sensitivity, and 77.6% specificity for RF while it resulted in an accuracy of 46.6%, sensitivity of 90.7% but the specificity was only 13.9% from SVM in predicting climate-smart technology adoption status In contrast, the k-nearest neighborhood algorithm only achieved 70.4%, 80.0%, and 63.4% accuracy, sensitivity, and specificity respectively; The climate-smart technology adoption status was predicted using naive bayes, which performed at 53.2% accuracy, 93.8% sensitivity and 12.5% specificity respectively. For the test dataset, the Cohen kappa statistics of Logistic regression (LR), Random Forests (RF), SVM (linear), K-nearest neighborhood (KNN), and naive bayes were 0.60, 0.75,4 40,5279 0535297,4 55. F1-Score of LR, RF, SVM, KNN, and NB was 79%, 88%, 65%, 76%, and 68% for the training data set, respectively. The Random Forest algorithm achieved the best accuracy among all other classifiers. Based on the analysis, we recommend extending LR to incorporate Bangladesh's important prior concern with predicting climate-smart agricultural practices such as shrimp aquaculture. For predicting the adoption of CSTs for increasing the productivity of shrimp in Bangladesh, RF and LR were relatively more conservative than any of the ML algorithms that we employed in this study.

Conclusions and policy implications

Abstract. There is a growing interest in understanding how local climate, socio-economic factors, and smartphone use influence farmers' adoption of Climate-Smart Agriculture (CSA) technologies; comprehensive knowledge is needed for future planning towards improvement of food security. Farmers' preference towards originating CSA technologies reflects climatic conditions and their risk perceptions. For instance, farmers in the study areas implement methods such as polyculture shrimp farming, dike netting to prevent escapement of shrimp, increased water level with tidal exchange (receiving brackish and river water through sluice gates), digging canals inside ponds during high temperature periods for keeping cool water, strengthening earthen dikes and integrating rice (drought-tolerant varieties or salt tolerant salinity resistant high-yielding) with prefab shrimp systems. The CSA technology preferences are similar in both research locations. Therefore, policies and programs that promote CSA technology should be targeted at site-specific and context-based solutions to the needs of local farmers. Application of a logit model confirms that CSA adoption is significantly influenced by socio-economic factors, such as age, education, landholding family size, and smartphone use in Ethiopia. The spectrum of need for CSA technology in various socioeconomic and geographic contexts calls for sound and equitable government actions. Thus, this paper primarily compares the effectiveness of various machine learning algorithms in predicting the adoption of climate-smart technology by Bangladeshi farmers because such understanding can help design appropriate agricultural climate-responsive intervention strategies. We applied five supervised machine learning ensemble algorithms to predict technology adoption in coastal regions. Symmetric551 In conclusion, we found that the random forest (RF) classifier exhibited the best results for predicting climate-smart technology adoption in shrimp aquaculture. This is a work that researchers should build on in the future. These findings can thus assist policymakers in designing programs that promote climate-invasive growth in developing nations.

CRediT authorship contribution statement

Md Mizanur Rahman Sarker: Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Supervision; Visualization; Writing - original draft; and Writing - review & editing

Aya Suzuki: Funding acquisition; Investigation; Validation; Visualization; Writing - review & editing

Ahmad Jainul Abidin: Data curation; Formal analysis; Methodology; Resources; Software

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