Evaluating Machine Learning Models for Optimal Livestock Environment Prediction in Smart Farming Applications to Enhance Food Security

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Abstract— **Livestock is a vital protein source for the global population and any disruptions of supply can significantly threaten national food security. Therefore, ensuring a stable and continuous livestock supply is essential. Researches have highlighted a strong link between livestock production and environmental factors and proposed several smart farming solutions to be adopted to effectively monitored and optimized livestock production. In this study, we propose the adoption of sensor technology and machine learning to establish optimal environmental conditions for livestock in Malaysia. Evaluation of various machine learning techniques is carried out to determine the most effective model for enhancing livestock production in the smart farming systems. This research simulates the livestock living environment equipped with sensors and selected parameters for data collection to be utilised in training the selected machine learning models which are Decision Tree, Naïve Bayes and K-Nearest Neighbours. The trained machine learning models are then applied in predicting the optimum environment for livestock using the dataset of simulated environment. Then, performance evaluation on the machine learning models was carried out. The accuracy results for Decision Tree, Naïve Bayes and K-Nearest Neighbours are 99%, 63% and 89% respectively. From the research, Decision Tree model is found to be the best performing model at predicting the optimum environment for livestock. These findings provide invaluable insight to advance researches on optimum livestock environment prediction in smart farming for Malaysia use case and will enable precise adjustments and monitoring to achieve ideal conditions for livestock growth to provide consistent livestock production.**

Keywords— **Food security; Environment; Livestock; Machine learning; Smart Farming.**

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I. INTRODUCTION

Food security is intrinsically linked to national security because a nation's stability and well-being are directly connected to a stable and reliable food supply. Food security also described as accessibility to physical and economical availability to safe, adequate and nourishing food to sustain nutritional requirements for an active and healthy life to everyone at any time[1][2]. Food security is one of the most basic and fundamental human rights, considering humans require food to survive and function. Food security has raised major concerns around the world as more countries have started to realise its importance at the turn of the 21st century during the pandemic COVID-19 which forces a lot of countries to reevaluate its food security strategy in times of emergencies due to the widespread famines in areas of crisis and natural disasters [3] [4] .

Researchers and policy makers discussed that food security can be achieved when a country is able to consistently produce or source more food than it consumes [2]. Having a stable food security is crucial to ensure a well-fed population. To combat food insecurity, the Malaysia government enacted a five-point security plan. The plan establishes tactics and programs to be carried out in order to ensure food security in Malaysia's agricultural sector, named "Malaysia's Agro-Food Policy (NAP 2011–2020) Performance and New Direction" [5]. Thus, food security which forms the basis of national security is our main motivation for this research. Meanwhile, since that livestock which includes poultry, cattle, goat and others, are the

main provider of proteins, comprising of more than a third of human protein consumption [6]. However, livestock are exposed to numerous risks including diseases. Thus, current research primarily focuses on disease detection such as detection of zoonotic diseases and how to prevent a disease outbreak and the effects of greenhouse gas emissions of livestock on the environment [6][7]. Our study found a significant gap in research regarding the determination of optimal environments for livestock farming, despite the environment's critical role in enhancing livestock production and stabilizing prices to ensure availability for the global population at affordable rates. While previous studies on smart farming have primarily focused on integrating sensor technology into livestock farming, there has been insufficient emphasis on fully leveraging data analytics derived from the sensor data. Thus, to address this gap, this research focuses on using the collected data to determine the best machine learning technique to predict the optimum environment for livestock to increase livestock production. In this research, we choose Decision Tree, Naïve Bayes and K-Nearest Neighbours for the machine learning model to understand the suitability of machine learning models for data for smart farming by measuring the performance, accuracy and precision of each machine learning technique using collected data. For data collection, we selected the most essential parameters which are temperature, humidity, carbon dioxide and ammonia based on findings in the literature review. Sensors was installed in our simulated smart farming to record data for temperature, humidity carbon dioxide and ammonia data.

This paper has four sections: Section I introduces the research. Section II highlights the materials and method used in this research. Section III evaluates the performance of each machine learning technique used, by providing analytical comparison and the discussion on the results. Section IV highlights the summary and the potential of this research, as well as the conclusion attained.

II. Material and Method

A. Food Security

The four pillars of food security serves as a guideline to evaluate a nation's food security [2]. The four pillars of food security are as follows:

i. Food availability: The availability of food in sufficient amounts and of decent quality, either sourced through domestic production or are imported from other countries. Availability does not correlate to fully domestic produce and countries can have good food availability from imported sources.

ii. Food access: The accessibility of nutritious food in adequate amounts by individuals. The access should not be limited by the individual's legal, political, social and economic status.

iii. Utilisation: Achieving a state of nutritional health involves meeting all physical needs through proper nutrition, including a balanced diet, access to clean water, sanitation, and healthcare. This shows that non-food inputs are crucial in food security.

iv. Stability: In order to achieve a state of food stability, a nation must ensure that its population is able to access sufficient food at all times. They should not experience famine or lose access to food supplies even through crisis, such as wars or cyclical events, such as seasonal monsoon or droughts. The stability concept can therefore be attributed to both food security aspects of availability and accessibility [2].

Food security in Malaysia is above average when compared to other countries as Malaysia was ranked the 41st out of 113 countries worldwide according to Global Food Security Index. Malaysia achieved an overall score of 69.9%, availability score of 59.5%, and quality and safety score of 74.7% [2]. According to the figures above, Malaysia is able to sustain two-thirds of its population at any given point. However, this does not translate to the ability to self-sustain its population. Malaysia's national self-sufficiency ratio (SSR) is only 57% according to the Supply and Utilization Accounts of Selected Agricultural Commodities. Moreover, Malaysia still heavily relies on imports for its most important food source, including crops, livestock and fisheries. Additionally, livestock such as mutton and beef, have the highest import dependency ratio (IDR) at 89.4% and 81.6% respectively in 2021. This shows that Malaysia have only managed to produce 10.6% of the mutton and 18.4% of the mutton that the population consumes. Fortunately, the poultry industry in Malaysia is faring better than its ruminant counterparts, producing almost all the chicken meat consumed at 99.9% and 114.4% of chicken eggs. The IDR for poultry is almost non-existent, barring just 6.1% while none for chicken eggs. The pork industry in Malaysia is pretty much self-sustaining, with 93.4% SSR and an IDR of 7.1%.

B. Livestock

Livestock in Malaysia is widely consumed as the primary source of meat-based protein. Per capita, Malaysians consume 92.3 kg of livestock products per year in 2021. From the overall of 92.3 kg, 46.6 kg is the production of chicken meat, 20.8 kg is the production of chicken and duck eggs, 5.5kg is the production of beef, while duck meat and mutton are 1.6 kg and 1 kg respectively. Livestock growth is affected by a lot of factors [8]. The parameters used in this research are temperature, humidity, carbon dioxide and ammonia levels as they are the most essential parameters [9][10][11][12][13]. Carbon dioxide and ammonia are considered greenhouse gases. Much of the research into the relationship between greenhouse gases and livestock are done to study on the effect of the greenhouse gases produced by livestock to the environment and not to the livestock themselves [6][14][15][16][17][18]. Most research on livestock using Machine Learning techniques are that of disease detections [7][13][19][20] and livestock monitoring [13][21].

From the literature review, we can conclude that livestock require specific ranges of carbon dioxide and ammonia levels, as well as particular levels of temperature and humidity to be healthy. The optimal environment for livestock is temperature of 30°C and lower, humidity level of between 40-60%, carbon dioxide levels between 400 and 1000ppm, ammonia levels of below 25ppm [9][10][11][12][13]. Higher temperature will

cause the livestock to be stressed and their growth will be impeded. A high humidity level and a high level of carbon dioxide and ammonia level will cause the environment to be a suitable hotbed for bacteria to thrive, potentially spreading zoonotic disease. The disease will easily spread in a humid environment, leading to premature death of the livestock.

C. Smart Farming

The concept of smart farming is rooted in the concept that fresh food can be grown year-round in urban areas, while utilising fewer resources, such as land, water, and chemicals. Smart farming also aims to minimise the distance food travels to reach consumers, thus, reducing food miles. The Smart Farming implementation discussed is able to increase efficiency compared to traditional farming. The United Nations (UN) stated that the growing global population serves as a catalyst for the surge in both food consumption and production requirements, with a potential increase of up to 70% by the year 2050. To meet these demands, a shift from conventional agriculture to smart farming is necessary. Therefore, utilising IoT technologies that would enable accurate data collection for data-driven decision-making processes is essential. The transition to smart farming will enable remote monitoring that can decrease production costs. It can also promote the adoption of efficient and sustainable agricultural practices that are in line with the demand and resource efficiency objectives of smart farming. Despite the challenges associated with adopting smart farming including the increased use of sensors that may pose security risks, the smart farming remains the most promising approach to enhancing livestock production. The implementation of smart farming techniques offers unparalleled opportunities for optimizing agricultural practices and ensuring the sustainability of food resources. Although the smart farming solution poses several potential vulnerabilities, including opening the attach vectors to the IoT devices, sensors and actuators through hardware layer, network layer and application layer, a comprehensive framework will be able to address this issue. Therefore, the benefits of smart farming in improving livestock yields and contributing to food security outweigh the potential drawbacks, making it a critical strategy for the future of agriculture [22][23][24]. However, smart farming introduces additional risks and threats due to the data storage and communication nature inherited. The limitations of IoT devices necessitate storing data in cloud computing facilities, making cloud security crucial [25]. Ensuring cloud infrastructure security is also crucial for smart farming environment. Furthermore, understanding cloud security implications is essential to protect data and address access control challenges [26][27]. Human factors, like cloud computing acceptance, must also be considered to mitigate security risks in training and analysis [28].

Researchers in [9][11][21] discussed on the implementations of sensory technology in monitoring farming environment, while researches in [10] discussed the use of fuzzy logic in calculating the ideal temperature and humidity for chicken coop. However, our research discusses that there is a gap from previous research, whereby the gathered data was not fully utilised. The collected data were only implemented for the farmers to be able to monitor their farming environment remotely. We observe that previous research only using collected information to adjust conditions to create an optimal setting and has not adequately addressed the utilisation of data for predicting the environmental changes in the livestock environment. Hence to address this gap, this research is utilising machine learning for predicting the optimum livestock environment.

D. Machine Learning

Machine learning (ML) is a system that makes decision and predictions through adaptability rather than being explicitly programmed. It automatically obtains and absorbs data through the understanding of patterns and relationships in data via the creation of algorithms [29]. The basis of this method is learning from training, observation, analysis and experience obtained from the data [30]. The outcomes from the analysis in ML demonstrate its ability to self-improve and its effectiveness. Through this technique, the future behaviour of data can be predicted without depending on a preset equation as a model. ML can be divided into two categories, namely supervised and unsupervised learning. Supervised learning generates predictions or classifications for new input data by utilising labelled data, as opposed to unsupervised learning which uses unlabelled data. Supervised learning is used for tasks that requires classification and regression [31]. Supervised learning has higher accuracy for prediction tasks as they are trained directly with labelled datasets, while unsupervised learning is used to find patterns and structures from the given data. Since this research focuses on training ML models to predict the optimum condition of the livestock environment using labelled dataset, supervised learning ML models are used. The ML models used in this research are the most commonly used ML models for supervised learning, which are Decision Tree (DT), Naïve Bayes (NB) and K-Nearest Neighbours (KNN).

Decision Tree: The Decision Tree model is a flowchart-like tree structured model of every possible decisions and their consequences [32]. It contains decision nodes to denote its attributes and edges for representing the attribute values. The Decision Tree model is an effective technique for constructing classifiers from data. The depiction of Decision Tree model as a tree structure helps classifying new data input by allowing it to construct decision rules.

Naïve Bayes: The Naïve Bayes model considers each feature as unique from one another. The model utilises the concept of a Bayesian approach on its probability calculations. The Bayesian approach uses the Bayes' Theorem to form predictions as more training is given, it combines the prior probability and conditional probability in a formula. The mathematical equation of the Bayes' Theorem is as follows:

$$P(x|Y) = \frac{P(Y|x)P(x)}{P(Y)} \quad (1)$$

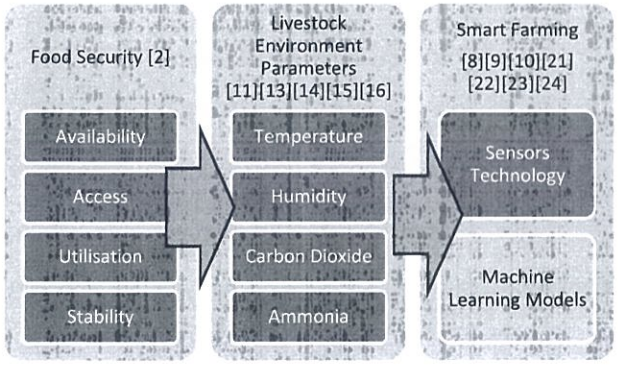
The equation displays P(x) as the prior probability of the feature set x regardless of label. P(x|Y) is the prior probability of feature set x given that label is Y. P(Y) is the prior probability that the label Y has occurred. The equation shows

the naive prediction process of assuming that all features are unrelated to one another, hence the "Naïve" in its name.

K-Nearest Neighbours: K-Nearest Neighbors model is an altered version of an instance-based learning algorithm that relies on feature-distinctions within a labelled dataset. The K-Nearest Neighbors model employs distance metrics to identify a group of K-samples which are the nearest to the new and unknown samples. This means that the K-Nearest Neighbors model identifies the K most similar instances which are nearest to the current point of data by using a labelled dataset. The model retains the complete training set in the training phase to be used in the next steps. As a result, the model forms a prediction by comparing the similarity of the newly input data to the training data. This is done by comparing each instance of the training data with labels of unknown samples or new input data and the prediction is obtained through calculating the mean of the response variables [32].

Based on related work that we referred, this study proposes the conceptual structure for Optimal Livestock Environment Prediction in Smart Farming to Enhance Food Security in Figure 1.

Fig 1. Conceptual Structure for Optimal Livestock Environment Prediction in Smart Farming to Enhance Food Security



Based on the related works that was discussed in previous section, we developed a conceptual structure that is substantially aligned with improving key elements of production stability and supply to enhance food security. This alignment is highly depending on the acquisition of sufficient data on the most suitable machine learning models to ensure the effectiveness in predicting optimal living environments for livestock. Based on this significant gap, we conducted an experimental analysis to evaluate the effectiveness of various machine learning models in predicting optimal living environments for livestock. Through this approach, we seek to generate important reference data that contribute to the existing body of knowledge. The experimental analysis is discussed in the following section.

E. Method

Fig. 2 shows the proposed Smart Livestock Farming System algorithm for farmers to optimise their livestock production. In this proposed Smart Livestock Farming System, the farm is set

TABLE I
ALGORITHM OF FARM ENVIRONMENT CONDITION GENERATION

Algorithm: Generate the output of the farm environment for the training dataset

Output: Condition of Environment for Livestock Farm
Start:
Input Data: Training set (Dataset collected from sensors in farm)
For each row in Training set do
If temperature = optimum AND humidity = optimum AND carbon dioxide = optimum AND ammonia = optimum then
    Farm environment = 1
Else Farm environment = 0
End if
End for
End

with DHT22 sensors to measure temperature and humidity levels and MQ135 Air Quality sensors to measure carbon dioxide and ammonia levels. The sensors above are used as they are compatible with the ESP32 microcontroller which is an Arduino module. The sensors are then connected to the ESP32 microcontroller. The data collected by these sensors in the farm is stored in the database from the ESP32 microcontroller via Hypertext Transfer Protocol (HTTP), for viewing and for generating the training dataset. The dataset is then fed to the Machine Learning models. The trained Machine Learning models will then analyse the data and provide predictions that can be utilised by the farmer for decision making. The optimum environment of the farm is determined by the combined measurement of temperature, humidity, carbon dioxide and ammonia levels in the farm from the values obtained in *B. Livestock*, with class 0 being not optimum and class 1 being optimum. The classes 0 and 1 are used so that it is easier for training the Machine Learning models. Then, the farmer is able to carry out corrective measures in the farm based on the predictions in real time. This means that the farmer could rectify the conditions of the environment in the farm immediately without having the livestock experience the stressful environment.

In this research, 5000 rows of temperature, humidity, carbon dioxide and ammonia levels data were collected from sensors throughout the farm over the course of one week in different weather conditions to simulate different conditions in the farm. The dataset is then filtered to remove duplicate data so that it only contains 5000 rows. The dataset is then identified as class 0 or 1 using the algorithm in Table I. The dataset is then used as the training dataset. The training dataset is then fed into the Machine Learning models for training. Once the Machine Learning models are trained, they are then tested with another dataset of 5000 rows of temperature, humidity, carbon dioxide and ammonia levels data collected throughout another week to evaluate its performance.

The Machine Learning models used in the experiment are having their performance evaluated in the final phase of this research as validation. After training the Machine Learning

models, the models are then put to the test to determine which among them are the best at predicting the optimum livestock condition when given the test dataset. Next, a confusion matrix is generated to evaluate the performance of each Machine Learning models. This is to determine the best model that produces the best performance based on the parameters in the training data. The confusion matrix is used to visualise the performance of the Machine Learning models by showing the effectiveness of the Machine Learning models at distinguishing between different classes, in this case, optimum and not optimum classes. The confusion matrix evaluates the True Negative (TN), True Positive (TP), False Negative (FN) and False Positive (FP) values of the predictions made by Machine Learning models. The aforementioned values are defined as:

- TN: The rate of correct predictions where the instances are of the negative class.
- TP: The rate of correct predictions where the instances are of the positive class.
- FN: The rate of incorrect predictions where the instances are falsely classified as the negative class, when they should be positive.
- FP: The rate of incorrect predictions where the instances are falsely classified as the positive class, when they should be negative.

The confusion matrix uses these values to calculate the accuracy, precision, recall and F1 score of the Machine Learning models. These paint a clearer picture for understanding the performance and behaviour of the Machine Learning models. The formulas used for calculating the accuracy, precision, recall and F1-score values of the Machine Learning models are as follows:

Accuracy is the ratio of the total amount of correct predictions (TN and TP) to the total amount of predictions (TN, TP, FN and FP) that the model made. This is to evaluate the overall accuracy of the model at correctly classifying all instances into negative and positive classes.

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \tag{2}$$

Precision is the ratio of True Positive (TP) predictions to the total number of total positive predictions (TP and FP) made by the model. This is used to evaluate the ability of the model to correctly predict positive predictions.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

Recall is the ratio of True Positive (TP) predictions to the actual number of positive instances (TP and FN) in the dataset. This is used to evaluate the effectiveness of the model at predicting all positive instances.

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

The F1 score is a metric for assessing a Machine Learning model's overall performance and is used to balance the trade-off between precision and recall scores.

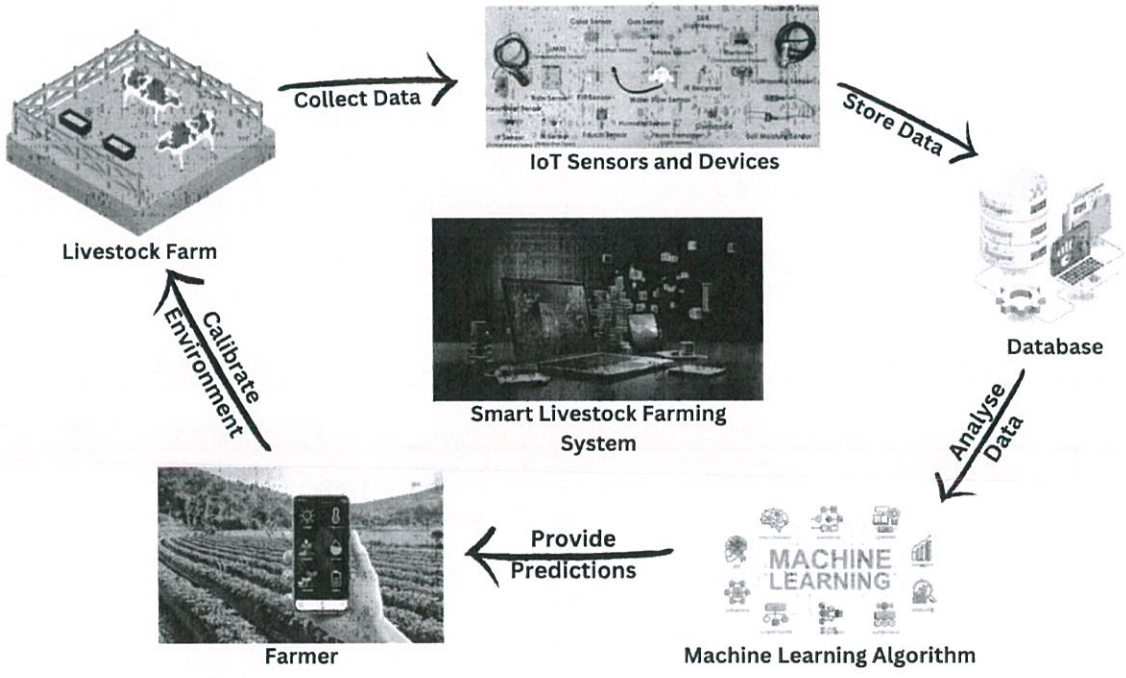


Fig 2. Proposed Smart Livestock Farming Ecosystem

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

By analysing the confusion matrix, this research is able to conclude the best model at determining optimum livestock environment in the next section.

III. Result and Discussion

The test results were accessed by comparing the true negative, true positive, false negative and false positive values, as well as the score of accuracy, precision, recall and F1 score of the three Machine Learning models (Decision Tree, Naïve Bayes and K-Nearest Neighbors). The score of accuracy, precision, recall and F1 are crucial for measuring and comparing the performance of model with another. The evaluation results of the Machine Learning models are shown in the following tables. Tables II, III and IV show the performance evaluation of the Naïve Bayes, Decision Tree and K-Nearest Neighbors model.

Table II shows the performance of the Naïve Bayes model. This model has a 0% false positive rate, which means it correctly classified all negative instances. The model has a high false negative rate of 36.36%, indicating that the model is falsely classified 36.36% of positive instances as negative. Overall, the model achieved an accuracy score of 64%, correctly classifying 64% of instances. The model scored 100% in precision, accurately identifying the positive class 100% of the time. The model has a low recall score of 31%, only managing to classify 31% of all positive instances. Subsequently, the F1 score of the Naïve Bayes model is at a relatively low score of 47%. This is due to the high disparity between the recall and precision scores.

By just looking at the perfect precision score, we can conclude that the model is actually doing well at predicting positive instances. However, that is not the case. By analysing the recall score, the Naïve Bayes model is in fact incapable of identifying positive instances, having only done so, 31% of the time. This means that the model will wrongly classify an optimum environment as non-optimum leading the farmer to incorrectly implement corrective measures on an otherwise optimum environment. The overall performance of the Naïve Bayes model is not up to par since it has a high rate of false negative and its inability to identify all positive classes results in a low recall and F1 score.

Table III shows the Decision Tree model achieving a near perfect 0% score for both false positive and false negative rate. The negligible false positive and false negative rate means the model has an overall accuracy of 100%, hence correctly classifying all instances. Subsequently, the model scored 99.84% in precision, accurately identifying the positive instances 99.84% of the time. The model achieved a near perfect recall score of 99.66%, accurately identifying 99.66% of all positive instances. The low disparity between the recall and precision scores means that the model achieved a F1 score of 99.75%. The Decision Tree model is able to correctly classify both negative and positive instances for 99.74% of the time, with minimal error made. The exceptional performance of the Decision Tree model is due to its simple yet effective algorithm.

Table IV shows the K-Nearest Neighbors model with a False Negative rate of 8.68% and a false positive rate of 2.06%. The model would wrongly classify a positive class 8.68% of the time, while a negative class is wrongly classified 2.06% of the time. As a result, the model achieved a modest overall accuracy of 89.26%, accurately classifying 89.26% of instances. The model scored 95.54% in precision, accurately identifying the positive instances 95.54% of the time. The model achieved a recall score of 83.59%, correctly classifying 83.59% of all positive instances. The K-Nearest Neighbors model has a recall score of 89.16%, indicating that the trade-off between precision and recall is not high. Overall, the K-Nearest Neighbors model has a moderate false negative rate while maintaining low false positive rate.

As a summary, the models performed relatively well in the test, with the exception of the Naïve Bayes model. The models are exceptional at predicting negative instances, with all models having low false positive score, with the Naïve Bayes model achieving 0% false positive score. However, the ability to accurately classify positive instances is somewhat ineffective, with the Naïve Bayes model recording the lowest recall score of 31.27%. Both the Decision Tree model and K-Nearest Neighbors model are on par with the requirement for the best machine learning model in predicting optimum livestock environment. They both have relatively low false positive and

TABLE II
Naïve Bayes Performance

DT	False Negative	False Positive
True Negative	47.02%	0.08%
True Positive	0.18%	52.72%
Accuracy	99.74%	
Precision	99.84%	
Recall	99.66%	
F1-score	99.75%	

TABLE III
Decision Tree Performance

NB	False Negative	False Positive
True Negative	47.10 %	0 %
True Positive	36.36 %	16.54 %
Accuracy	63.64 %	
Precision	100 %	
Recall	31.27 %	
F1-score	47.64 %	

TABLE IV
K-NEAREST NEIGHBOURS PERFORMANCE

KNN	False Negative	False Positive
True Negative	45.04 %	2.06 %
True Positive	8.68 %	44.22 %
Accuracy	89.26 %	
Precision	95.54 %	
Recall	83.59 %	
F1-score	89.16%	

false negative rate and both models possess high scores of accuracy, precision, recall and F1-score. However, there is a clear gap between both models that indicates that the Decision Tree model is the better model. The false positive and false negative rate of the Decision Tree is negligible. However, the same cannot be said for the K-Nearest Neighbors model, while low, it is still somewhat a noticeable error. The accuracy, precision, recall and F1 scores of the Decision Tree model are a near perfect of 100%, while the K-Nearest Neighbors model's score is only around the 90% mark, still considerably better than the Naïve Bayes model.

The most important factor when considering the best machine learning model for predicting optimum livestock environment is the ability of the machine learning model to accurately classify instances into the different classes. The inability and the ineffectiveness will lead to high false positive and false negative rates, which will mislead the farmer when monitoring and managing the livestock environment. A false positive prediction will lead the farmer into falsely believing that the farm's environment is optimum and not carry out any actions to calibrate the environment. While a false negative prediction will lead the farmer to mistakenly carry out corrective measures in order to optimise the farm's environment. By considering all the factors, this research concludes that the Decision Tree model is the best machine learning technique at predicting optimum livestock environment.

IV. CONCLUSION

This research aims to play a role in improving food security by increasing livestock production, thus lowering costs and making livestock more affordable by adopting the smart farming solution that incorporates machine learning. This research focused on the gap in selecting the most accurate model for machine learning by performing an evaluation in 3 models of machine learning.

This research compares and evaluate the performance of machine learning models at predicting optimal conditions for livestock in smart farming environment for the selected parameters of temperature, humidity, carbon dioxide and ammonia level. This research successfully compared and determined the best machine learning model to be used in predicting optimum livestock environment, which is the Decision Tree model. This research concludes that the Decision Tree model has the best performance in predicting both instances without positive bias. The simplicity of the Decision Tree algorithm allows it to correctly and effectively classify all instances into positive and negative classes with very minor false positives and negatives.

As future work, more parameters will be used in our smart farming simulation for more comprehensive data collection for Malaysia use case in predicting the optimum environment of livestock. The current parameters of temperature, humidity, ammonia and carbon dioxide levels form the rudimentary basis of environment factors affecting the livestock, which is also the limitation of this research. More comprehensive parameters can be added to represent the factors affecting the livestock environment more adequately, thus improving the accuracy of predicting the optimum environment for livestock. Additionally, adoption of technology also can be other perspective that can be taken into consideration. Understanding constructs for technology adoption, acceptance and readiness levels in smart farming also another areas that potential as future areas to be studied. [33]

Examining the cybersecurity aspects of smart farming solutions is crucial to comprehensively understanding the associated threats. More study to address this gap will provide insights into potential vulnerabilities and inform strategies to mitigate risks, ensuring the secure implementation of smart farming technologies that will also improve the food security strategy of a nation. Also, security issue including protecting infrastructure, understanding security implications and addressing human factors towards digital hygiene are essential to be addressed to mitigate risks in this advanced agricultural environment.

Overall, this research possesses the potential to drastically enhance the capabilities of predicting optimum livestock environment, which can in turn optimise livestock production, which is crucial for maintaining food security of the livestock sector for anyone that relies on it as their diet, source of income and livelihood. Proposed future work can provide more comprehensive structure to the body of knowledge.

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