Egg Incubation Automated Hatching System Naïve Bayesian

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***Abstract*—In recent times, efficient egg incubation has become crucial to ensuring the success of poultry breeding operations. Early detection and continuous monitoring of egg automatic detection using Artificial Intelligence (AI) can be costly. To address the challenges related to the Naïve Bayes Classification Method, early detection and automation of egg incubation yield more accurate results, and the collection of documents is more secure. Moreover, Min-Max Normalization eliminates duplicate data, minimizes unknown data, and maximizes valuable data during the preprocessing phase. Additionally, the Estimation of dew-point temperature measures humidity and vapor and tests the ratio between the processes. Ultimately, the proposed method classifies data, tests it, and validates the predicted data for performance. Calculation is a training process, while the testing data is multi-level in the classification process. Each type of data is given for the individual network connection of the classification data. It calculates comprehensive monitoring based on input data from video testing of the training data. Initially, it identifies nearby objects, children, and other elements to assess the effectiveness of these activities. The process offers greater reliability and achieves high performance while maintaining standard scalability. These techniques reduce time complexity, and performance remains within an accurate range of 91%.**

***Keywords*— Naïve Bayesian, data preprocessing, data normalization, Estimation of dew-point temperature, data classification.**

I. INTRODUCTION

The Internet of Things (IoT) measures temperature and humidity, as well as the duration of performance. Deep Learning (DL) analyzes real-time data, automatically detecting processes [1]. It utilizes Convolutional Neural Networks (CNN), with all data collected through the connected network and maintaining the incubator's temperature at a normal level [2]. The system employs temperature and humidity sensors to monitor the incubator's conditions and automatically adjust them to create an optimal environment for the eggs Image processing techniques observe all the data in the images while monitoring performance continuously. The helps in detecting and preventing issues early in the techniques and comparing all types of data in the automated incubation of eggs.

Automatic detection performs accurately in Artificial Intelligence (AI) and is one of the advanced technologies that provide high protection. It effectively checks the input to ensure proper results throughout the process by comparing it to previous and subsequent data while testing and validating to enhance reliability and maintain high scalability [3]. Support Vector Machine (SVM) handles non-linear data using kernel functions that map the data into a higher-dimensional space where it can be linearly separable. The multitasking performance is complete for every critical situation, easily managed by any of the applications suited for these techniques. The methods build a state network connecting the automatic systems that incubate and hatch eggs.

Automated incubators are generally more costly than manual incubators, posing a significant burden on small farmers with limited budgets. The technical complexity can also result in equipment or system errors, potentially leading to hatching failures [4]. The risk of accidental damage during egg turning or other automated processes persists in areas with unreliable power grids, primarily in rural or remote regions. Extreme variations in incubation temperature can affect the embryo and ultimately influence post-hatch performance. The process becomes particularly challenging for large datasets due to the demands of quadratic programming

optimization [5]. Additionally, the power modules can be pricier than using individual discrete components. Challenges arise with systems that involve multiple interacting variables or constraints, and overfitting can occur during model training with the data.
The main contribution focuses on data preprocessing, which involves converting raw data into a usable and analyzable format. The testing and validation of the humidity, which can be expressed as the ratio between the vapor, water, and temperature of the performance. The model is trained and tested on labeled data to learn the relationship between features and classes, and the class with the highest calculated probability is chosen as the prediction.

II. LITERATURE SURVEY

According to reports, unfertilized duck eggs and early-dead embryo eggs can significantly harm normally developing embryos if not detected and removed promptly. The process is time-consuming and requires more manpower. The proposed method describes an improved algorithm for the early detection of incubation in eggs using the YOLOv7 network. However, the process is highly expensive and has low standards for the stability of the process.
The fertility of hatching eggs, classified into fertile and dead eggs, is analyzed more accurately and effectively using a method that combines a convolutional neural network (CNN) with continuous monitoring of both the surface and inside of the eggs' shells. However, this process requires high computational cost. The proposed method is a sequential convolutional neural network, referred to as E-CNN, that calculates the heartbeat and duration of the performance. However, overfitting occurs during model training with the data.
Temperature and humidity are the most critical factors that must be controlled during egg incubation. The influence of the ECU on various systems can be compromised, resulting in unknown and unpredictable data handling characteristics [8]. The proposed method involves constructing an electronic module, with the individual components of the electronic system having been designed and developed. However, the process is especially the power modules, which can be more expensive than individual discrete components.
The electric bulbs are used to design and develop an egg incubator system capable of continuous monitoring and automatic detection of performance. Its measurement of temperature is a complex process and more time-consuming. The proposed method is a PID (Proportional-Integral-Derivative) controller implemented in a microcontroller. The controller design, based on these models, was created using MATLAB Simulink. However, the processes struggle with systems involving multiple interacting variables in egg incubation performance.
Develop a smart egg incubator that incorporates IoT technology and fuzzy logic, automatically regulating temperature and humidity during the process. The proposed method, a YOLOv9-S model, enables real-time chick detection and classification, enhancing monitoring and decision-making in hatcheries [10]. It reduces chick mortality and increases operational efficiency. However, the process cannot comprehend relationships between different regions or objects in a scene.
Environmental biomonitoring embryos can bioaccumulate and are highly sensitive indicators of performance, with greater complexity reflecting a higher level of environmental impact on performance. The proposed method measures the bioaccumulation of organic contaminants, including polycyclic aromatic hydrocarbons (PAHs) and phenolic compounds, and evaluates their potential effects on the testing and validation of performance. However, the level of environmental pollution is significant, and a considerable amount of noise occurs in the techniques.
The use of computer vision (CV) technology and automation to monitor and collect eggs is crucial for enhancing labor productivity in egg-laying breeding and improving data prediction during the egg incubation process. However, insufficient or unbalanced datasets can result in biased models that perform poorly in specific groups or scenarios [12]. The proposed method utilizes the EXPMA (Exponential Moving Average) to measure time, temperature, and air. However, this process has higher time complexity and a lower level of secure processing.
The greenhouse interaction of age-related effects can be accurately measured in terms of time, air, and temperature of performance, as well as the lack of transparency in the data and the high level of environmental impact processes [13]. The proposed methods for detecting and preventing egg incubation are essential; however, especially in small cages, flies may struggle to spatially segregate from the process.
In productive sectors, adopting Artificial Intelligence (AI)-based innovative systems for predicting days

and times more accurately enhances performance, albeit at a higher cost. The proposed method measures vapor, temperature, and air levels, while also reducing the time complexity of the process. However, the process becomes challenging, particularly for large datasets, because of the requirements for quadratic programming optimization.

The data from the temperature and humidity sensor (DHT11) is sent to the Arduino Nano controller for processing, measuring the temperature data to collect from the process. However, the implementation of the process is complex. The proposed method involves using a DC motor for measuring temperature, vapor, and caution during the testing and validation of the process. Nevertheless, DC motors may have limitations in power output compared to AC motors, especially at higher speeds.

III. PROPOSED METHODOLOGY

The focus is identifying unknown data, addressing missing values, and measuring the prediction values. Describes relative humidity, which can be expressed as the ratio of water vapor to the temperature of the performance. It is trained and tested on labeled data to learn the relationship between features and classes, with the class with the highest calculated probability being the prediction.

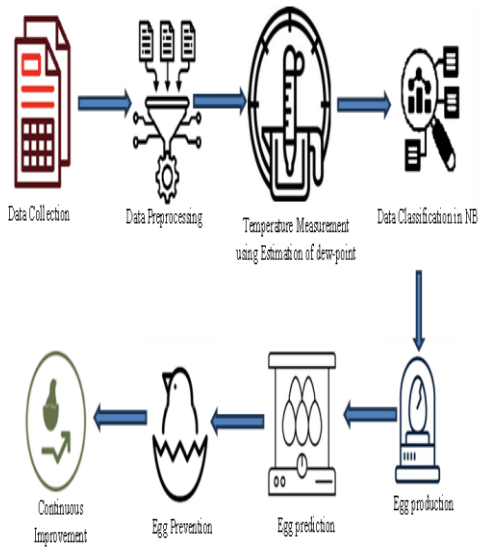

Fig. 1. Egg Incubation Automated Hatching System Using Naïve Bayes

Figure 1.1 entails cleaning, transforming, and preparing the data for analysis and interpretation , and to measuring humidity, which can be expressed as the ratio of water vapor to the temperature of the performance., with the class exhibiting the highest calculated probability being the prediction.

A. Dataset Description

The section is a data attribute that can include factors like size, color, shape, and potential defects. By employing advanced image analysis and pattern recognition, the system accurately and efficiently distinguishes between various egg types, ensuring consistent quality control and optimization in fields such as agriculture, food production, and poultry farming. The automation streamlines egg sorting processes, reduces human error, and boosts overall productivity.

	A	B	C	D	E	F	G
1	observed_r	percent_h	percent_e	source			
2	31-12-2007	3.2	NA	Egg-Markets-Overview-2019-10-19.pdf			
3	31-12-2008	3.5	NA	Egg-Markets-Overview-2019-10-19.pdf			
4	31-12-2009	3.6	NA	Egg-Markets-Overview-2019-10-19.pdf			
5	31-12-2010	4.4	NA	Egg-Markets-Overview-2019-10-19.pdf			
6	31-12-2011	5.4	NA	Egg-Markets-Overview-2019-10-19.pdf			
7	31-12-2012	6	NA	Egg-Markets-Overview-2019-10-19.pdf			
8	31-12-2013	5.9	NA	Egg-Markets-Overview-2019-10-19.pdf			
9	31-12-2014	5.7	NA	Egg-Markets-Overview-2019-10-19.pdf			
10	31-12-2015	8.6	NA	Egg-Markets-Overview-2019-10-19.pdf			
11	30-04-2016	9.9	NA	Egg-Markets-Overview-2016-12-02.pdf			
12	31-08-2016	10.13569	9.634938	computed			
13	31-08-2016	12	NA	Egg-Markets-Overview-2016-12-02.pdf			
14	30-09-2016	10.05704	9.557439	computed			
15	31-10-2016	12.29353	11.60231	computed			
16	30-11-2016	12.10062	11.37289	computed			
17	31-12-2016	11.79349	10.92237	computed			
18	31-12-2016	12.3	NA	Egg-Markets-Overview-2019-10-19.pdf			
19	31-01-2017	11.81985	11.13466	computed			
20	10-02-2017	12.7	NA	Egg-Markets-Overview-2017-02-10.pdf			
21	28-02-2017	12.15251	11.49596	computed			

Fig .2. Egg Production Dataset

Figure 1.2 involves cleaning, transforming, and preparing the data for analysis and interpretation. Its calcuationis a humidity, which can be expressed as the ratio between the vapor, water, and temperature of the performance. The probability of a given instance belonging to a particular class is determined by examining the probabilities of its features.

B. Analysis Data Preprocessing

The section is data preprocessing, which entails converting raw data into a usable and analyzable format. It includes cleaning, transforming, and preparing the data for analysis and interpretation. The focus is identifying unknown data, addressing missing values, and measuring the prediction values. Equation 1 states that data collected in the real world often contains missing and noisy values. Identifying and cleaning this noisy data is essential. Let's assume the p,q input data.

$$p = (p_1, p_2, \dots . p_n), q = (q_1, q_2, \dots q_n) \qquad (1)$$

Equation 2 is a data reduction in the features and instances section of the performance calculation. It minimizes the unknown data while maximizing the process's original data.

$$s(p,q) = \sqrt{\sum_{i=0}^{n}(p_i - q_i)^2} \quad (2)$$

Equation 3 normalizes the data and is a form of the minimum-maximum data calculation for testing performance. Let's assume the G(s)=Normalization data.

$$G(s) = \sum_{i=1}^{n} -x_i log_2 x_i \quad (3)$$

Equation 4 signifies that the overall prediction is a normalization of the data and validation of the product level.

$$Gain\ (p,q) = G(s) - \sum_{p\in q} \frac{|p|}{|q|} G(T) \quad (4)$$

C. Estimation of dew-point temperature

The section outlines the temperature at which air and water are measured during the process. It covers the maximum and minimum levels of vapor, water, and temperature performance. The calculation represents a ratio between temperature, vapor, and water.

Equation 5 describes relative humidity, which can be expressed as the ratio between the vapor, water, and temperature of the performance.

$$Kp = 100\frac{e}{e_s} \quad (5)$$

Equation 6 is a latter that can be calculated as e = actual water vapor pressure and e = saturation water vapor pressure.

$$e_s = 6.1078\ exp^{17.269}\frac{T}{T+237.3} \quad (6)$$

Equations 7 and 8 state that when the temperature is at its daily minimum (Tn) and water vapor is saturated, the time is denoted as (Td).

$$T_P = T \quad (7)$$

$$T_h = T \quad (8)$$

D.Naïve Bayesian Classification

The section functions as a classifier that calculates the probability of a given instance belonging to a particular class by examining the probabilities of its features. It is trained and tested on labeled data to learn the relationship between features and classes, and the class with the highest calculated probability is the prediction.

Equation 9 shows that each pair of features to be categorized is independent. Suppose x is an n-dimensional value and y is the class variable.

$$X(q|p) = \frac{X(q|p)X(p)}{X(q)} \quad (9)$$

Equation 10 involves finding the class Y with the highest probability, and the data can be processed continuously or discontinuously.

$$p = (p_1, p_2, p_3, \dots . p_n)$$
(10)

Equation 11 includes various predictors and data points, requires less training data, accommodates both discrete and continuous data types, and predicts enhanced runtime performance; let's assume the X(y) = prediction data variables.

$$y = X(y)\prod_{i=1}^{n} X(q|p) \quad (11)$$

IV. RESULT AND DISCUSSION

This section evaluates the precision, recall, accuracy, FN, and time complexity scores across various parameters and approaches. Furthermore, the proposed method can detect data transmissions using IoT technology and data points in the attack dataset.

Table 1. Simulation Parameter

Simulation Process	Parameter Name
Dataset Name	Data Production Dataset
No of Dataset	97
Training Dataset	57
Testing Dataset	40
Language	Python

As illustrated in Table 1, the simulation parameters were evaluated using 97 data collected in the feature selection process. 57 is a training dataset, and 40 is a testing dataset.

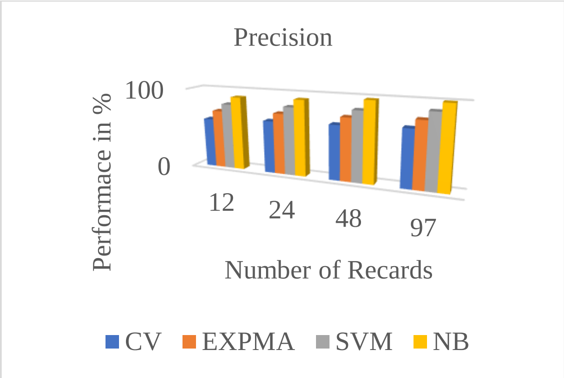

Fig. 3. Analysis of Precision

Figure 1.3 illustrates using precision analysis for secure health data exchange through Artificial Intelligence technology. This review assesses previous methods, including CV, EXPMA, and SVM contrasts them with the proposed NB method. The precision levels of the performance ratings for these methods are 85.6, 89.9, and 99.2, respectively, for the various performance levels in data protection.

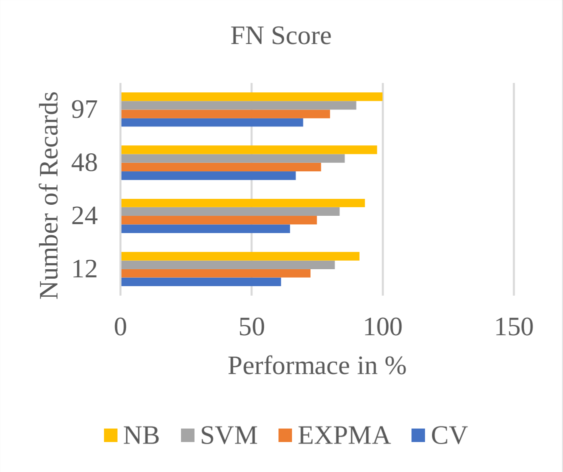

Fig .4. Analysis of FN Score

Figure 1.4 illustrates using FN Score analysis for secure health data exchange through Artificial Intelligence technology. This review assesses previous methods, including CV, EXPMA, and SVM contrasts them with the proposed NB method. The precision levels of the performance ratings for these methods are 85.6, 89.9, and 99.2, respectively, for the various performance levels in data protection.

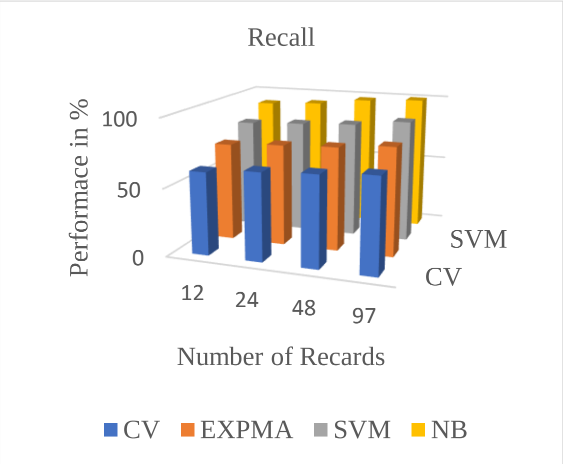

Fig .5. Analysis of Recall

Figure 1.5 illustrates using recall analysis for secure health data exchange through Artificial Intelligence technology. This review assesses previous methods, including CV, EXPMA, and SVM contrasts them with the proposed NB method. The precision levels of the performance ratings for these methods are 85.6, 89.9, and 99.2, respectively, for the various performance levels in data protection.

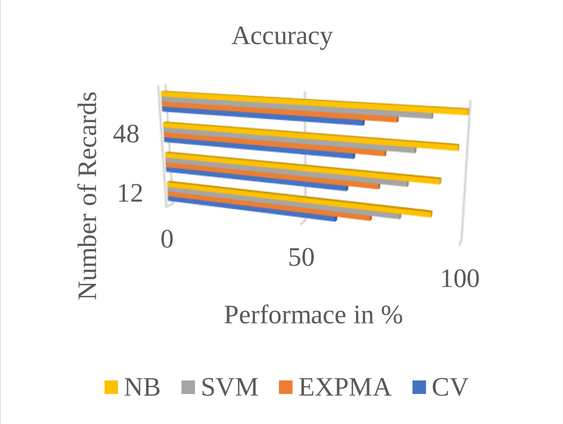

Fig .6. Analysis of Accuracy

Figure 1.6 illustrates using accuracy analysis for secure health data exchange through Artificial Intelligence technology. This review assesses previous methods, including CV, EXPMA, and SVM contrasts them with the proposed NB method. The precision levels of the performance ratings for these methods are 85.6, 89.9, and 99.2, respectively, for the various performance levels in data protection.

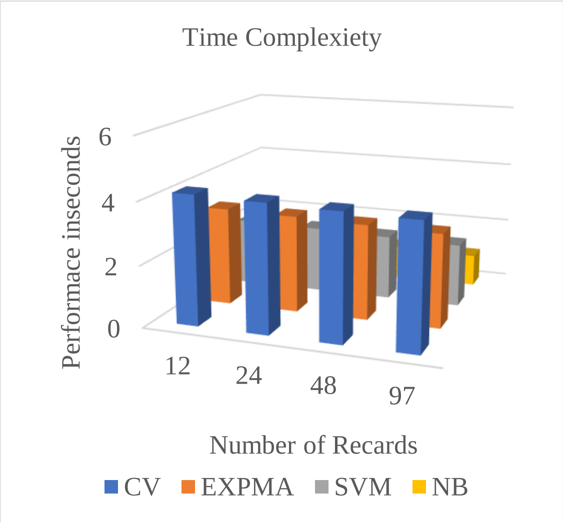

Fig .7. Analysis of Time Complexity

Figure 1.6 illustrates using time complexity analysis for secure health data exchange through Artificial Intelligence technology. This review assesses previous methods, including CV, EXPMA, and SVM contrasts them with the proposed NB method. The precision levels of the performance ratings for these methods are 5.56, 3.45, and 1.50, respectively, for the various performance levels in data protection.

V. CONCLUSION

This study explores the crucial role of technology in enhancing detection, prevention, and response in egg incubation and automated hatching operations. Prediction analysts engage with automated egg incubation detection and maintain monitoring to enhance performance. Performance measurement is improved using the F1 score, time complexity, recall, precision, and accuracy based on commonly employed real-time data for result comparison. The capacity to identify unknown data is bolstered by compressing vast amounts of information into manageable archives and transforming the data. This process involves further classification and reduction of the data. It is trained and tested on labeled data to ascertain the relationship between features and classes, with the class having the highest calculated probability as the prediction. Additional tasks involve continuous monitoring over a specified period, concentrating on egg incubation and other monitored activities. The process is managed efficiently, completed within a defined time frame, and performed with multitasking efficiency, ensuring reliability. The system has achieved a 91% accuracy rate in automated egg incubation detection.

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