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E-nose-based Optimized Ensemble Learning for Meat Quality Classification

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Abstract. One of the most important sustainable development goals is eliminating hunger. Meat is an essential source of protein for the human body, which aids in its health. Because it is a perishable product, it was vital to keep an eye on meat quality. In this paper, a dataset has been obtained that expresses the meat's quality. This dataset represents the measurement of several sensors that measure the gases emitted from meat, which we consider as an electronic nose (E-nose). Several single machine learning algorithms have been used to classify meat quality. These algorithms are Logistic regression (LR), Random Forest (RF), K-Nearest Neighbor (KNN), and Decision Tree (DT). The complex voting ensemble learning algorithm was employed in conjunction with the E-nose. E-nose's ensemble learning accuracy using complex voting ensemble learning techniques was 99.57%, which is superior to the average performance of the other single machine learning classifiers. Grid search is used to tune the ensemble algorithm's hyperparameters, better results are obtained, and this outcome is reached when the ensemble is soft. The result was 99.9%.

Keywords: Food security, E-nose, sustainable development, ensemble learning, hard voting, machine learning

1. Introduction

Food security is one of the goals that help accomplish the Sustainable Development Goals' second target of zero hunger. According to the Food and Agriculture Organization of the United Nations (FAO), improper food poses a hazard to human health and economies worldwide, with an estimated 600 million instances of food-borne infections each year. As a result, ensuring food safety is a top priority for public health and a critical step toward achieving food security (https://www.fao.org).

Quickly, accurately, and automatically determining food quality is a practical requirement in everyday living. Numerous studies have been conducted on the quality of vegetables, fruits, meats, and aquatic products (Lei Zhou et al., 2014). Electronic nose (E-nose), computer vision, spectroscopy, spectral imaging, and other modern approaches have been employed to detect food qualities.

The E-nose is proving to be a reliable tool for supporting sensory evaluation when it is related to food scent analysis. When it comes to food aroma analysis, the E-nose is proving to be a viable instrument for aiding sensory evaluation. Chemical gas sensors on the E-nose may capture volatile chemicals and then produce an olfactory pattern of the volatiles to help distinguish the samples. It's simple to use, impartial, and inexpensive. The E-nose is now used in various food quality control applications, including beverages, meat, dairy, fruit, tomatoes, red ginseng, tea, and rice plants(Huaixiang Tian et al., 2014).The meat of high quality has the potential to alleviate hunger and poverty. It should be viewed as a weapon for eradicating hidden hunger (Voster Muchenje et al., 2015).

To ensure the quality of meat, various studies have been carried out.For example, the researchers in (B. W. Penning et al., 2020) used image analysis and the rapid evaporative ionization mass spectrometry for deciding the meat quality. Machine learning (ML) was utilized in both cases to improve the speed and accuracy of carcass quality assessment.

Computer vision with artificial intelligence techniques is widely used to determine the freshness of meat. Here, meat means beef, poultry, and fish. The researchers in (Erika Carlos Medeiros et al., 2020) presented 31 studies that use computer vision and artificial intelligence to explore various meat quality aspects. Another work presented by researchers in (Devin A. Gredell et al., 2019) demonstrated how Rapid Evaporative Ionization Mass Spectrometry (REIMS) could be used to obtain molecular scale data as an objective measure for evaluating beef quality features. Eight alternative machine learning methods were tested to classify beef quality parameters to construct predictive models using REIMS data. The E-nose is proving to be a viable instrument for aiding sensory evaluation. It's simple to use, impartial, and inexpensive (Huaixiang Tian et al., 2014). In several cases, an ensemble of numerous different machine learning techniques has outperformed individual machine learning models in overcoming individual machine learning models' challenges and improving classification efficiency (Muhammad Pervez Akhter et al., 2019).

This work suggested an E-nose system based on optimized voting ensemble learning for meat quality classification to achieve sustainable development. The following parts of this paper are organized as follows. In Section II, the background of the improved technology is briefly discussed. In Section III, the proposed model is discussed. In Section IV, the results of the experiments are discussed. The conclusion and future work are found in Section V.

2. PRELIMINARIES

2.1. Electronic nose

The term "electronic nose" (E-nose) refers to gas sensors that monitor the surrounding gaseous environment based on the idea that changes in the gas atmosphere have a predictable impact on sensor quality. Metal oxides, conducting polymer composites, and inherently conducting polymers are three types of materials that have been created for a range of sensor types. Apart from conductive sensors, optical sensors, gas-sensitive field-effect transistors, surface acoustic wave sensors, and quartz microbalance (QMB) sensors have all been used to detect gas. The most promising developing technologies in this field are Micro Electro Mechanical Systems (MEMS) and nanotechnologies. The term E-nose has also been applied to systems that use ultra-fast gas chromatography or mass spectrometry to detect substances. The E-nose systems need an appropriate post-processing mechanism to interpret and classify the data acquired from the individual sensors in the array (Amy Loutfi et al., 2015).

Several researchers have used the E-nose to assess the type and quality of food. We will show some of them. In (Baietto M. et al., 2015), the authors investigated using E-nose devices (with customized sensor arrays) as potentially effective tools for more efficient fruit fragrance analysis to replace traditional, expensive approaches. E-nose data on the efficiency of this specific gas-sensing technology for fruit identification, cultivar distinction, and ripeness evaluations, as well as fruit quality in business marketplaces, was also highlighted in this research. The authors in (Nahid Aghilinategh et al., 2015) employed E-nose with machine learning approaches to detect the five ripeness classes of berries.

The researchers in Wojciech Wojnowski et al., 2015) demonstrated that evaluating poultry meat quality can be done using ultra-fast GS, which allows for a speedy and accurate forecast of the product's shelf-life. A dedicated E-nose with a range of chemical sensors may be the best solution when money is limited. Chemical sensors lack the sensitivity of gas chromatography detectors, but they can produce trustworthy results when used with competent chemometric analysis of their response signals.

An E-nose has also been used to identify volatile chemicals produced by food-borne bacteria in tainted cattle. Other E-nose uses include seasoning and grading profiling in beef and poultry products, spoiling profiling in beef products, and storage period differentiation in fish and eggs (Fady Mohareb et al., 2016).

2.2. Machine Learning approaches —Single Classifiers

Logistic Regression (LR): is one of the most widely used algorithms. LR is frequently the first choice for programmers when it comes to predictive learning. Furthermore, a probabilistic classification model can forecast and categorize the objective (B. Krishnapuram et al., 2005) (J. Kuha et al., 2020).The logistic function P of the LR is utilized to assess the LR, which may be found in Equation (1).

$$p = \frac{\exp(s)}{(1+\exp(s))} \tag{1}$$

p is the probability of the observed data, while S denotes the estimated value and is calculated using the following Equation.

$$S = \beta 0 + \beta 1X1 + \beta 2X2 + \dots\dots\dots + \beta nXn \tag{2}$$

where $\beta 0$ is the initialized fixed value determined by the algorithm, βi is the coefficient of the Xi independent variable, and n is the number of training factors.

K-Nearest Neighbor Classifier: Classification using the KNN algorithm is one of the most basic and extensively used methods in the field. It looks for the dataset's nearest neighbors to estimate (H. Patel et al., 2019). The KNN algorithm is a nonparametric and slow learning method. Lack of training period for laziness because it "memorizes" rather than "learns" the training data, it is called "Memory-Based Classification."

Random Forest Classifier: A tree-based ensemble uses a random variable set for each tree. Finding a f(x) that can forecast y is the goal. The prediction function is derived from the loss function L(y, f(x)) in order to minimize the loss EXY (l(y, f(x)). As an intuitive measure of how near one individual's value of f(x) is to another individual's value of y, L(y, f(x) is used. The letter L is frequently used in the context of squared error loss.

$$L(y, f(x)) = (y - f(x))^2 \tag{3}$$

and regression (S. Benbelkacem et al., 2019).

$$L(y, f(x)) = (y.f(x))^2 \tag{4}$$

Decision Tree: The decision tree classifier utilizes the correct method for solving the problem for basic and common classification issues. In contrast to other nodes in the tree, the roots of the decision tree classifier do not have any incoming edges. Nodes having outward edges are referred to as "internal" or "test." The leaves represent the nodes that have survived. Each decision tree internal node divides the instance space into two or more sub-spaces using a discrete function of the input values. In most cases, a single attribute is evaluated by each test. Therefore the instance space is divided according to the attribute's value. The condition necessitates a choice in the case of numerical attributes. Each leaf is allocated to a group or class using the essential target value as a guide. The leaf may also include a probability vector showing the probability that the goal value will have a given value. Instances are categorized according to the distance they travel from the root of the tree to the leaf based on the tests conducted along the way (L. Rokach et al., 2005) (L. Rokach et al., 2007).

2.3. Ensemble Machine Learning Methods

Ensemble learning is a subset of machine learning that refers to a method for enhancing model performance by merging many predictions. It comprises a trained base classifier whose decisions are combined to provide new results (Huazhou Chen et al., 2021). The natural reason for the ensemble process comes from human nature and our propensity to collect and weigh multiple viewpoints to make a complex decision. The ensemble learning was improving the performance for the following reasons:

- **Overfitting avoidance**: When just a small volume of data is provided, a learning algorithm is prone to find a slew of hypotheses that accurately forecast all the training data while making poor predictions for unknown situations. By averaging different hypotheses, the chance of selecting an inaccurate hypothesis is reduced, and the overall prediction performance improves.
- **Computational advantage**: Single learners may become caught in local optima when conducting local searches. Ensemble approaches reduce attaining a local minimum by mixing numerous learners.
- **Representation**: Anyone's model's space may not include the best hypothesis. The search space can be expanded by merging several models, resulting in a better match to the data space (QianruZhai et al., 2020).

There are two types of ensemble learning methods: parallel ensemble and sequential ensemble. The base-predictors (individual machine learning algorithms) are trained based on data inputs in parallel in the parallel ensemble. Simultaneous predictions are possible with the parallel ensemble because it uses several CPU cores to run the models simultaneously and uses their independence. The base-predictors are trained progressively in the sequential ensemble, resulting in one base-predictor plus the input data passing into the next base-predictor (Muhammad

Pervez Akhter et al., 2019). Simple (Max Voting, Averaging, Weighted Averaging) and Advanced (Stacking, Blending, Bagging, Boosting) ensemble learning approaches are the most common (Baba NM et al., 2020).

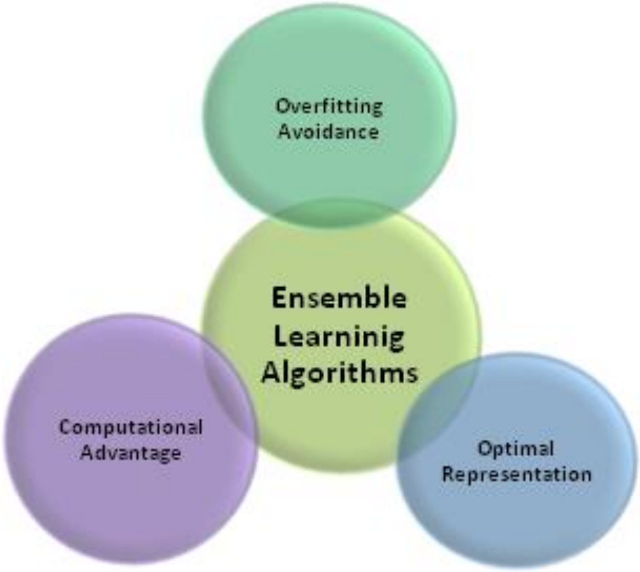


Fig. 1: Advantages of Ensemble learning algorithm

2.4. Grid search

Exhaustive grid search divides the searched parameters into grids of the same length within a particular range. As a result, it is possible to find the ideal solution by iteratively navigating over the grid (Yuting Sun et al., 2021). The algorithm is running as follows:

- **Step 1:** Initialization: The cross-validation means square error (CVMSE) is initialized as CVMSEr. Additionally, a step size d is specified to facilitate the search for values of parameters C and g within the range [2^{Cmax}, 2^{Cmin}] for C and [2^{gmax}, 2^{gmin}] for g;
- **Step 2.** Calculate the optimal point and update the CVMSEi using K-CV. If $CVMSE_i$<$CVMSE_r$ for a minimization issue, the optimal point is updated as $CVMSE_r$ = $CVMSE_i$, C_r = C_i, and g_r = g
- **Step 3:** If all parameters within the range have been searched, the simulation is stopped and the ultimate optimal point is achieved; otherwise,
- **Step 4:** return to step 2.

2.5. Model evaluation

Four evaluation indexes are used to evaluate the proposed approach's prediction ability in the classification problem: accuracy, precision, recall, and F1-score. Accuracy is the ratio of correct forecasts to all predictions, usually expressed as a percentage and determined using equations (5). Precision is a metric that assesses a model's ability to correctly forecast values in a given category and is calculated using equations (6). The fraction of successfully recognized positive patterns is measured by recall, which is determined using Equation (7). As seen in Equation (8), the F1-score is the weighted average of precision and recall.

$$Accuracy = (TP+TN)/(TP+FP+FN+TN) \quad (5)$$
$$Precision = TP/(TP+FP) \quad (6)$$
$$Recall = TP/(TP+FN) \quad (7)$$
$$F1\text{-}score = 2\times (Recall \times Precision) / Recall + Precision \quad (8)$$

True positive samples are TP, true negative samples are TN, false positive samples are FP, and false negative samples are FN (Omer Sagi et al., 2018).

3. Proposed E-nose-based ensemble learning for meat quality classification

The proposed model as seen in Figure 2 consists of several phases. The Ensemble Learning Approach, which incorporates numerous machine learning models, is known as the Voting Classifier.

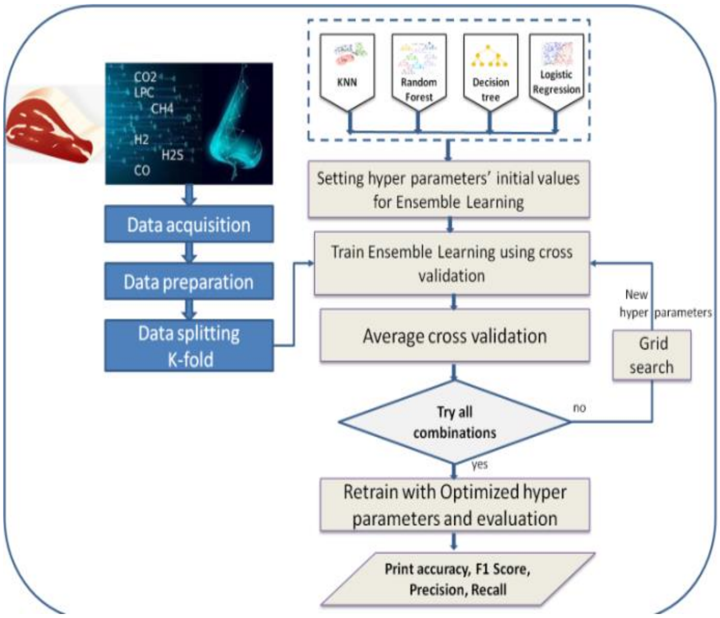


Fig. 2: The proposed E-nose-based ensemble learning for meat quality classification

Hard voting and soft voting are the two main forms of voting. The Ensemble Learning approach uses hard voting to assign a class label to the sample, which is determined by a majority vote. Four of the seven models, for example, identify the same sample as belonging to Class K1, whereas the other three models identify it as belonging to Class K2. Class K1 would be awarded to that sample because the majority voted for it. Soft voting considers all projected outputs, such as class labels, and allocates the sample to the class with the highest likelihood Y. Xiong et al., 2019).It's a hybrid of the mean and weighted majority voting methods. Instead, then using class labels, it applies weights to continuous outputs directly.

To solve the problem of meat quality classification, we combined the LR, Decision Tree, KNN, and Random Forest methods in this paper. We used a hard voting classifier because our dataset is labeled (i.e., discrete output), refer to Figure 4.The classifier's outputs are m1, m2, m3, and m4, which relate to excellent, good, acceptable, and spoiled, respectively. If m1 is the output of classifier1, m2 is the output of classifier 2, m3 is the output of classifier3, m2 is the output of classifier4 and m4 is the output of classifier 5, according to hard voting ensemble algorithm, the output will be m2.

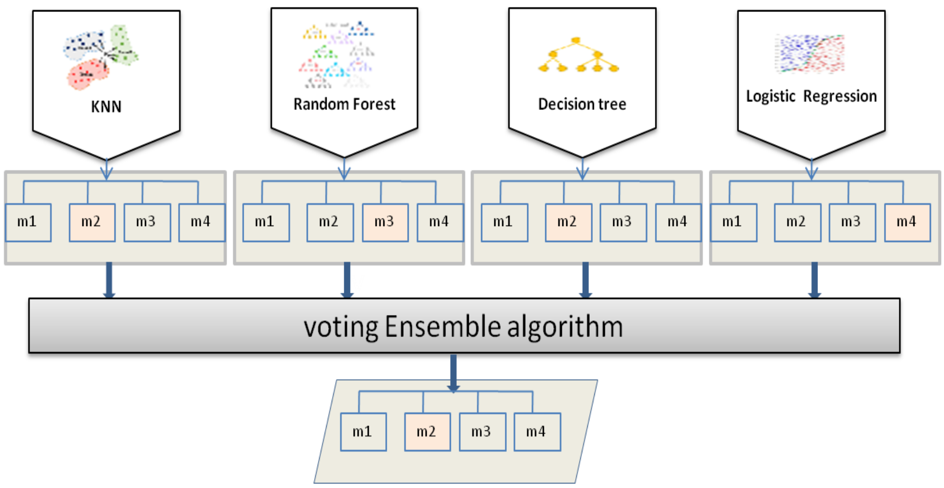


Fig. 3: Hard voting ensemble algorithm for meat quality classification

K-fold cross-validation is a technique for detecting overfitting and assessing the consistency of a model. In this paper, 10-fold cross-validation is employed. In the validation, the data is partitioned into K equal sets. The remaining sets are used as training data, with each of the K sets being used as testing data once. To acquire the final judgment of the trained model, an evaluation of the proposed classification model was conducted.

The Ensemble Learning method uses the training data to train each model individually. The Ensemble Learning approach feeds the testing data to the models after the training process, and each model predicts a class label for each sample in the testing data. Following that, each sample estimate is subjected to a voting process.

4. Experiments, results and discussion

The experiments were performed using tensor flow and Keras with google colab environment. The next two scenarios will be discussed. We use the dataset published in (Dedy Rahman Wijaya et al., 2018). The dataset consists of five recorded time series, each corresponding to five beef cuts and 2160 minutes of measurement points. The data contains; the reading values for the sensors in Table 1, time of measurement point (minutes), and Class label of beef quality ('excellent', 'good', 'acceptable', 'spoiled').

Table 1. List of gas sensors.

Gas sensor	Selectivity
MQ135	Carbon dioxide(CO2), ammonia(NH3), Nor, alcohol, ben- zene, smoke
MQ136	Hydrogen sulfide (H2S)
MQ2	Liquefied petroleum gas(LPG),I-butane, propane, methane, alcohol, hydrogen, smoke
MQ3	Methane(CH4), hexane, LPG, CO, alcohol, benzene
MQ4	Methane(CH4), natural gas y
MQ5	LPG, natural gas, town gas
MQ6	Propane, LPG, iso-butane
MQ8	Hydrogen(H2)
9 MQ9	Propane, methane, CO
DHT22	Temperature, humidity

We've gathered the five portions of the described dataset, each of which has 2,160 rows, totaling 10,800 rows. Table 2 shows the measurements of the 10 sensors, and Table 2 shows the category names with the number of each category.

Table 2. Prepared dataset.

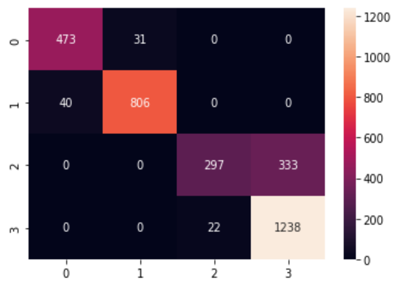
Class name	Number of class members
excellent	1680
good	2820
acceptable	2100
spoiled	4200
Total	10800

Scenario 1: Experiments for each individual model for the entire classifiers; LR,KNN, RF and DT.A 10-fold cross validation procedure is used to evaluate the approach's performance. Table 3 shows the experimental results for the individual classifiers. Figure 4 shows the confusion matrices.

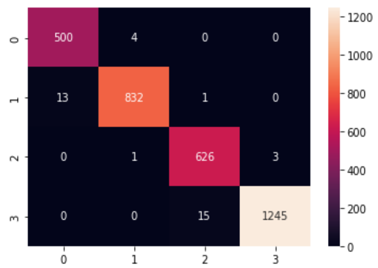
Table 3: Meat quality classification results using different classifiers

classifier / Evaluation	LR	KNN	RF	DT	Average
Precision	86.85	98.85	99.84	89.38	93.73
Recall	86.85	98.85	99.84	89.38	93.73
F1 Score	86.85	98.85	99.84	89.38	93.73
accuracy	86.85	98.85	99.84	89.38	93.73

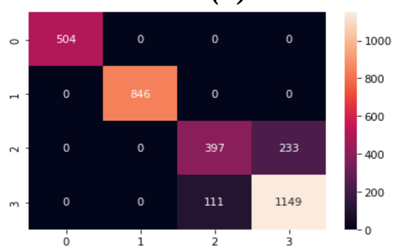
(a)



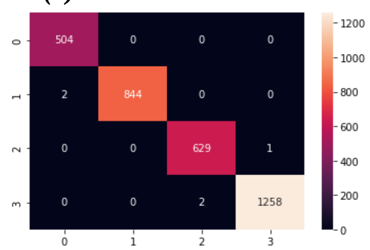
(b)



(c)



(d)



(e)

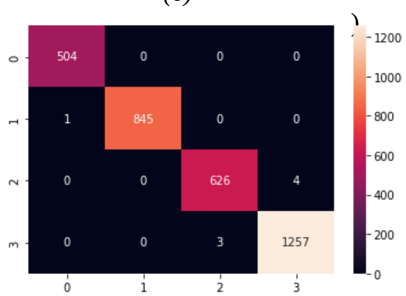


Fig. 4: Confusion matrixes (a) LR, (b) KNN, (c) DT, (d) RF and (e) Ensemble learning confusion matrix

Scenario 2: The model is built using an ensemble classification strategy. It uses the independent ensemble methodology, which uses numerous classification techniques simultaneously. The LR algorithm, KNN method, RF method, and DT method are all implemented in the model. Each composite classifier is trained on the same training set in a single run. The ensemble classifier is created by combining all of the composite classifier's outputs into a single prediction. This ensemble classification strategy combines the outputs of numerous independent classifiers to increase performance. A 10-fold cross-validation procedure is used to evaluate the approach's performance. The hyperparameters of ensemble learning classifiers were; voting='hard',flatten_transform='false', and n_jobs=17. Table 4 shows the hard voting ensemble classification results, and Figure 5 shows its confusion matrix.

Table 4.Ensemble learning results

classifier / Evaluation	Hard voting Ensemble classifier
Precision Score	99.75
Recall Score	99.75
F1 Score	99.75
accuracy	99.75

The results of using hard ensemble learning algorithms show that the ensemble learning accuracy was 99.57% which is better than the average performance of the individual classifiers.

Scenario 3: The method of parameter tuning known as "grid search" involves creating and evaluating a model for each possible combination of algorithm parameters given in the form of a grid (Ranjan G S K et al., 2021). Grid search is a type of parameter optimization technology. It will be used to optimize the parameters of all spectroscopy-relevant analytical procedures in the future (Ranjan G S K et al., 2021). It is envisaged that most parametric chemometric algorithms would incorporate this method. Co-optimization can be improved by identifying a potential value for each algorithm's configurable parameters. Initially, the grid search was exhaustive across a predefined subset of the hyper-parameter space. To begin, each modeling parameter is set to a value within a predetermined range. The hyper-parameters are described in their minimum (lower bound), maximum (upper bound), and several steps. Three different scales can be used: hard and soft for type of voting; false and true for flatten transform; finally, n_jobs have ranged from 0 to 30 scales. The performance of every combination is evaluated using some performance metrics.

The algorithm's output performs best when the following parameters are used: n_jobs=9, voting type=soft, and flatten transform type=true. The accuracy of the optimized ensemble results is 99.9%.

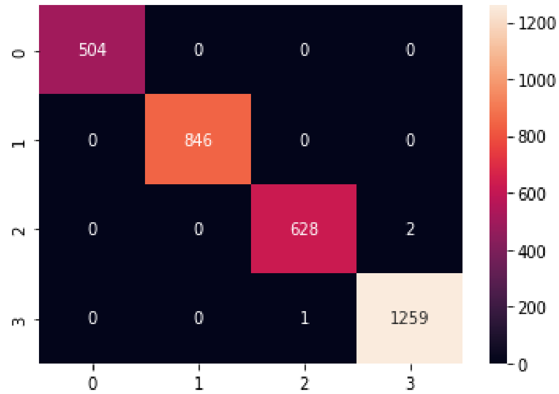


Fig. 5: Optimized Ensemble learning confusion matrix

5. Conclusion and Future work

The elimination of hunger is one of the most important sustainable development goals, and meat is a key source of protein for the human body, which aids in its health. Because the meat is perishable, it was critical to watch its quality. In this investigation, the E-nose, which consists of a collection of sensors and is distinguished by its low cost and speed of classification, was used. The E-nose was used in conjunction with the hard voting ensemble learning method. E-nose's ensemble learning accuracy was than the average performance of the other machine learning classifiers. When grid search is used to tune the ensemble algorithm's hyperparameters, better results are obtained, and this outcome is reached when the ensemble is soft. Author plans to expand this research in the future by predicting the conditions that cause the meat to spoil.

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