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ORIGINAL

Research on fresh image recognition algorithms based on machine learning

Investigación sobre nuevos algoritmos de reconocimiento de imágenes basados en aprendizaje automático

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ABSTRACT

The identification of fresh images tackles issues related to accurate classification, speed and flexibility enhancement, and perhaps superior food safety evaluation. In this work, the type and freshness identification (TFI) system is based on ML (machine learning). The research suggests ML techniques for identifying various meats (pork, chicken, beef, etc) flaws and differentiating between fresh and decomposing meats to decrease labour expenses, manufacturing time, and worker effort. An efficient TFI system is suggested in this work using machine learning (ML) techniques. We gather various meat samples to effectively identify the type and freshness of the meat. Pre-processing of raw images is conducted to standardize the raw data samples. In the feature extraction process, features from the normalized data are extracted to confirm the quality of the data. The retrieved data is divided into categories for fresh meat and non-fresh meat. The suggested approach is used to evaluate TFI efficiency using a Python program. In conclusion, it was discovered that this study outperformed in improving the TFI performance.

Keywords: Type and Freshness Identification (TFI); ML (Machine Learning); Meats; Pre-Processing; Feature Extraction.

RESUMEN

La identificación de imágenes frescas aborda cuestiones relacionadas con la clasificación precisa, la velocidad y la mejora de la flexibilidad, y tal vez la evaluación de la seguridad alimentaria superior. En este trabajo, el sistema de identificación de tipo y frescura (TFI) se basa en ML (machine learning). La investigación sugiere técnicas ML para identificar diversas carnes (cerdo, pollo, tern, etc) defectos y la diferenciación entre carnes frescas y en descomposición para reducir los gastos de mano de obra, el tiempo de fabricación, y el esfuerzo de los trabajadores. En este trabajo se sugiere un sistema eficiente de TFI utilizando técnicas de machine learning (ML). Recogemos varias muestras de carne para identificar eficazmente el tipo y frescura de la carne. El pre-procesamiento de las imágenes raw se lleva a cabo para estandarilas muestras de datos raw. En el proceso de extracción de características, las características de los datos normse extraen para confirmar la calidad de los datos. Los datos recuperados se dividen en categorías para carne fresca y carne no fresca. El enfoque sugerido es usado para evaluar la eficiencia de TFI usando un programa Python. En conclusión, se descubrió que este estudio superó en mejorar el desempeño del TFI.

Palabras clave: Identificación de Tipo y Frescura (TFI); ML (Aprendizaje Automático); Carnes; Pre-Procesamiento; Extracción de Características.

INTRODUCTION

In determining the meat's freshness in the prior scenario, indicators were the amounts and make-up of particular volatile gas indicators that were noted throughout storage. Hydrogen sulphide (H2S) gas is an important gas for determining freshness and identifying meat deterioration.[1] Meat producers, vendors, and consumers pay close attention to meat freshness since it is a crucial determinant of safety and quality of meat products. Measuring meat freshness traditionally involves sensory analyses, chemical analyses, and microbiological analyses. Human senses are used in sensory evaluations to gather data on the colour, flavour, suppleness, and general quality of the meat. But there are a lot of drawbacks to sensory analysis, like the expensive expert team. Chemical techniques are exact and objective, although they are typically applied in time-consuming and hazardous laboratories. Additionally damaging and time-consuming for bacterial culture, microbiological counting techniques are unable to deliver fast and accurate test results. Thus, to guarantee the superiority and protection of meat, it is essential to explore original techniques designed for quick, affordable and harmless meat originality testing.[2]

Significant progress has been achieved in deep learning (DL) across a range of applications, as well as expected language dispensation, feature extraction, and classification of images and segmentation.[3,4,5,6] The non-destructive testing methods that employ the recognition of images for food standard evaluation and protection management can benefit from the use of transfer learning in the development of DL scaffolding.[7] TFI is a methodology or system designed to categorize and ascertain the type or nature of an item, as well as determine its age or level of freshness. This method characteristically involves a categorization technique to recognize the group or type to which an item belongs and methods to measure its sequential relevance or exchange. TFI systems are often used in different domains such as data retrieval; content administration and invention quality management.[8]

Recent trends in meat freshness and identification focus on smart packaging technologies like time-temperature, gas, and pH indicators, blockchain for traceability and fraud prevention, IoT and sensor technologies for real-time monitoring, DNA bar-coding for species and pathogen detection, and AI for predictive models and quality control. Consumer demand for sustainability, transparency, and ethical practices is rising, alongside stricter regulatory compliance and the adoption of global standards to ensure meat safety and quality.[9] The goal of the project is to create and examine ML-driven DCRF algorithms that will enable precise evaluation of meat freshness, improve dependability, cut down on waste, and guarantee both consumer safety and high-quality, safe meat products.

From ideation to execution, this work proposed a novel notion for Food Standards Agency (FSA) -assisted DL in meat freshness perceptive observation.[10] Methods were created for the live tracking of meat quality throughout the whole process, from planning to execution. Ayam6Net a self-made, basic architecture, was used to train the dataset of images of chicken meat.[11] For comparison, they also employed the architectures of Alex Krizhevsky Network (AlexNet), Visual Geometry Group Network (VGGNet), and Google's Lecun Net (GoogLeNet). Positioned on the experiment result, they can declare with the reason of structural design with a changeable pixel dataset gives results with better accuracy than other designs and image datasets of dissimilar sizes. The recommended technique offers a way to assess the freshness of mutton and offers an industrial establishment for investigating previous aspects of meat. An absolute freshness display called Total Volatile Basic Nitrogen TVB-N, or total changeable basic nitrogen, was estimated for mutton using an amalgamation of electronic nose (E-nose) and hyper spectral image (HSI).[12]

This work provides an establishment for further research into the myoglobin data connected to meat cleanness. By analyzing myoglobin data and reflection spectra diagonally a variety of freshness stages, the DL-based representation was accomplished by determining the beef's freshness.[13] Developed utilizing a deep convolutional neural network (DCNN) and located on pictures of ordinary carp taken. To use the suggested technique of categorizations fish photos according to freshness, characters from the photographs were first mechanically filtered using the Visual Geometry Group 16-layer network (VGG-16) design.[14]

This study presented an autonomous technique that uses image processing and a mixed DL representation to organize fish freshness. For feature extraction, the simultaneous long short-term memory construction ML approach and the VGG-16 neural network architecture are employed.[15] Provide a DL-based computer vision method that uses the CNN approach to identify the freshness of fruit.[16] Then, using publicly available datasets of both fresh and rotten fruits for classification obtained from Kaggle, the specifically created CNN model was assessed. This study proposed an E-nose system based on CNN that classifies food freshness based on time series data.[17] In addition, it can distinguish between the meat and the body component, a feat unprecedented among other researchers. Although packaged meat products can readily deteriorate, anthocyanins can be utilized as a pH-sensitive substance to show freshness. The pigments must be contained in a suitable matrix. In this work, low-acyl gellan was stabilized by adding raspberry anthocyanins , which were suggested as a potential freshness indication.[18] The creation of a precise yet user-friendly technique to evaluate food freshness has been highly demanded. In this study, they demonstrated an ML approach positioned on CNN to analyze the spectrum to

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detect the freshness of food.[19] CNN model has been used to determine the variety of fruits and vegetables. Next, the suggested structure uses actuators and sensors to measure the quantity of food degradation while monitoring fruit and vegetable gas emissions, temperature, and humidity.[20] In addition, this would regulate the environment and, if feasible, prevent food spoiling.

In this research, they examined the effects of six different spectral pre-treatments on the partial least-squares regression (PLSR) modelling Savitzky Golay smoothing, normalized mean entering, multiple scattering correction (MSC), 11-point moving-average smoothing and standard normal variants (SNV) conversion.[21] In this research, the freshness of pork is classified into five levels based on TVB-N content.[22] Various DL networks, such as GoogLeNet, VGG, and Residual Network (RestNet), are used to train the photos. A novel, enhanced neural network is constructed to expect the freshness of pork after the training conditions of each network are examined. This allows for the absorption of the advantages of many networks.

METHOD

Using deep convolutional gated recurrent units (DC-GRU) in conjunction with random forest enables accurate prediction of the type and freshness of meat, combining temporal data processing capabilities with robust ensemble learning for comprehensive quality assessment. To meet industrial needs for efficiency and precision, our hybrid model combines the temporal knowledge of DC-GRU with the ensemble learning of random forests to improve accuracy and dependability in the assessment of meat quality. Figure 1 debits the principle elements of the proposed method.An environment compatible with Python 3.11.4 was used to construct the necessary processes. Replicating the examination of the recommended optimization choices was a Windows 11 laptop with 32 GB of RAM and a processor Intel i5 11th Generation CPU.

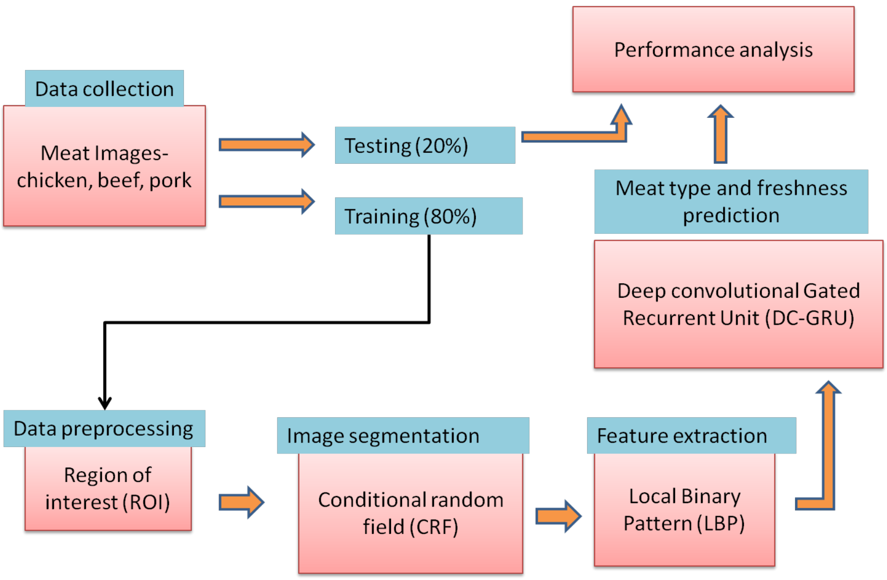

Figure 1. Meat type and freshness prediction workflow

Data collection

In this study, the varieties of meat examined like beef, pork, and chicken. We bought samples of meat from various vendors in the city market. Obtaining meat photos requires a few procedures. Initially, the meat portion is split into many pieces, resulting in 15 segments of meat slices. The meat is set up at room temperature, which is 28 ´C. Secondly, the method involves capturing a chicken using a 200x magnification digital microscope and camera. The goal is to eliminate the many lighting and environmental factors that affected the acquisition of the meat flesh picture. The freshness of five categories is used in this study to identify meat: extremely fresh, fresh, moderate-fresh, not too bad and adulterated.

Data pre-processing

To enhance deep learning model performance, the data set is fed into the system for pre-processing. For the purpose of accelerating convergence, the preprocessing phase in this paper involved standardizing the data. Normalizing image pixels from 0 to 1 using an equation (1) is the foundation of this technique.

$$I' = I/255 \qquad (1)$$

Where the input image is called I, the normalized image is called and 255 represent the highest intensity value per pixel in the grayscale image.

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Image segmentation using Conditional Random Fields (CRF)

After the preprocessing, the segmentation done by CRF can be used to fine-tune the outcomes and guarantee spatial consistency. CRFs can help smooth out segmentation borders and enhance the precision of freshness recognition by simulating the connections between nearby pixels, particularly in areas with noisy or unclear boundaries. In equation (2) the CRF takes into account the log-loss of the total energy given X = $\{x_j\}$, a collection of image occurrences with associated tags y = $\{y_j\}$, where j indexes images.

$$O(Z|W;X) = \frac{1}{A}\exp\left(-\sum_j F\left(Y_j, X_j; W\right)\right) \qquad (2)$$

With (A) serving as the normalization term and (w) as the parameters, the model achieves better generalization. The force E of an image x over the superpixels N and limits S with segmentation labels y is articulated as follows in equation (3).

$$F(Z,W;X) = \sum_{O\epsilon\mathcal{N}} \Phi^{(1)}\left(z^o, W; X\right) + \sum_{(O,R)\epsilon\mathcal{S}} \Phi^{(2)}\left(z^O, z^r, W; X\right) \qquad (3)$$

The unsigned and pair wise potentials, denoted by $\Phi^{(1)}$ and $\Phi^{(2)}$, are dependent on the parameter w and the observations x and y, respectively. A two-step procedure is primarily involved in CRF's search for the best labelling to produce Maximum a Posterior. Identifying the generally expected brand for the experiment data based on the erudite parameters; obtaining the mathematical model characteristics from the training data. Consequently, the segmentation problem has been simplified to decreasing the energy across y by the parameters w that were learned, in equation (4).

$$Z^* = arg \min_{Z\in z} F\,(Z,W;X). \qquad (4)$$

Feature extraction using Local Binary pattern (LBP)

LBP is a grayscale invariant measure of texture. The 3×3 neighborhood that surrounds each pixel is used for the basic LBP to function. Using equation (5) as a guide, the mask is used to compare each surrounding pixel with the center pixel to produce a binary pattern: it is possible to use a wide variety of variables for feature extraction. Mathematical features are divided into two categories: global and local. Among them are the following:

$$e\left(J(y_0), J(y_j)\right) = \begin{cases} 1, if J(y_j) - J(y_0) > \text{threshold} \\ \quad 0, if J(y_i) - J \le \text{threshold} \end{cases} \qquad (5)$$

j = 1 to 8 The position of the neighbouring pixels is represented, and the central pixel is indicated by y_0. The general formulation of LBP about radius q and neighbor o is provided by equation (6).

$$LBP_{O,Q} = \sum_{o=0}^{o-1} T(h_o - h_d)2^o \qquad (6)$$

h_o -Indicates the pixel's grayscale
h_d -Represents the color temperature of the focal point

Meat Type and freshness prediction using Deep Convolutional Recurrent Forest (DCRF)

Meat Type and Freshness Prediction using Deep Convolutional Recurrent Forest (DCRF)" refers to the application of a specialized ML model combining deep convolutional neural networks (CNNs) with recurrent neural networks (RNNs) in a forest ensemble framework. This approach aims to accurately classify different types of meat and assess their freshness based on visual and temporal data patterns, addressing quality control needs in the meat industry.

Meat Type using Deep Convolutional Gated Recurrent Unit (DC-GRU)

The DC-GRU technique is used for detecting the type of meat. DL techniques are always being improved and new structures and methodologies are being explored for problems such as image categorization, which includes differentiating between different kinds of meat. A function e is created to reflect the relationship among well-log data W and the goal variable Z_c at depth c in the framework of type identification utilizing a network, as demonstrated in equation (7):

$$Z_c = e(W,c) \qquad (7)$$

It is difficult to derive directly because of the very nonlinear structure of f. Consequently, employing a Deep Neural Network (DNN) to approximate e is more practical. By examining data patterns and mapping them appropriately, DNNs can estimate V_s, as shown in equation (8):

$$f_\theta: W, c \rightarrow Z \qquad (8)$$

It is possible to train the DNN to estimate the mapping to V_s, as shown by equations (7) and (8). To get this approximation, the network parameters are optimized during the training process. The depth organization matrix W for a set of data is defined in equation (9).

$$W_c = (w_1^n, w_{2,\ldots}^n w_c^n, \ldots . w_C^n) \qquad (9)$$

Depth c values are contained in the set equation (10) and principles at these depths are contained in the set W^n values, such as:

$$W^n = (w_1^n, w_{2,\ldots}^n w_c^n, \ldots . w_C^n \qquad (10)$$

V_p the historical data of the anticipated V_s is represented by the equation (11).

$$W = \begin{bmatrix} w_1^1 w_1^2 \cdots w_1^n \\ w_2^1 w_2^2 \cdots w_2^n \\ \vdots \quad \vdots \quad \vdots \quad \vdots \\ w_c^1 w_c^2 \cdots w_c^n \\ \vdots \quad \vdots \quad \vdots \quad \vdots \\ w_C^1 w_C^2 \cdots w_C^n \end{bmatrix} \qquad (11)$$

Freshness prediction using Random forest (RF)

One type of supervised learning method is Random Forest (RF). Data is categorized using Random Forests using a sequence of decision trees. Every Decision Tree is trained using the Random Forest approach, which involves randomly assigning individual samples to groups. In the collection of trees during the classification phase, the bulk of opinions are cast by individuals. Several, identical trees make up the RF. As long as a tree with variables x and y can be created, the tree will continue to grow. It is feasible to deduce the existence of fresh growth by observing the nearby trees, even though it is isolated from any additional trees in the vicinity. The only choice available is Tree X. Higher accuracy is achieved with a RF since each node is assigned an unpredictable number of offspring. Using this strategy, one can randomly select data qualities to construct root, within, and/or leaf branches. The highest point of the decision tree is the main branch. Within the internal branch, there is one input and one or more outputs. A leaf, also known as a terminal node, is a node with one input and no output. Algorithm 1 can be utilized to construct individual trees.

Algorithm 1: Random Forest

Input: $(b,a)^l$
L: Instance with K features
m: number of labeling instance
J: Iteration count
begin
for x€{1,......N}
do $c_{w\leftarrow}$ 0
for x€{1,......N}
do
for x€{1,......1}
do
b_1←Arbitrary instance from b^l
x←m(x_1)
b_2←Arbitrary instance from b^l
b_1 (w)←b_2 (w)
if m(b_1)≠x
then
c_w←c_w+1

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RESULTS

Accuracy, specificity, sensitivity, and precision are metrics used to evaluate the predictive capabilities of DCRF models in tasks related to identifying meat type and assessing freshness. Proposed (DCRF) method was compared with some existing techniques such as Support Vector Machine (SVM),[19] RF,[19] Partial Least Squares Discriminant Analysis (PLS-DA),[19] and 1-Dimensional Squeeze-and-Excitation Residual Network (1D-SE-ResNet).[19] Table 1 shows a summary of the experimental findings.

Confusion matrix: by correlate the expected and authentic set labels; the true positives, true negatives, false positives, and false negatives of a classification model are displayed in a table called a confusion matrix. The confusion matrix for estimating the freshness of meat suggests the following classes: Extremely Fresh, Fresh, Moderately Fresh, Not So Fresh, and adulterated. Figure 2 shows the confusion matrix for meat freshness.

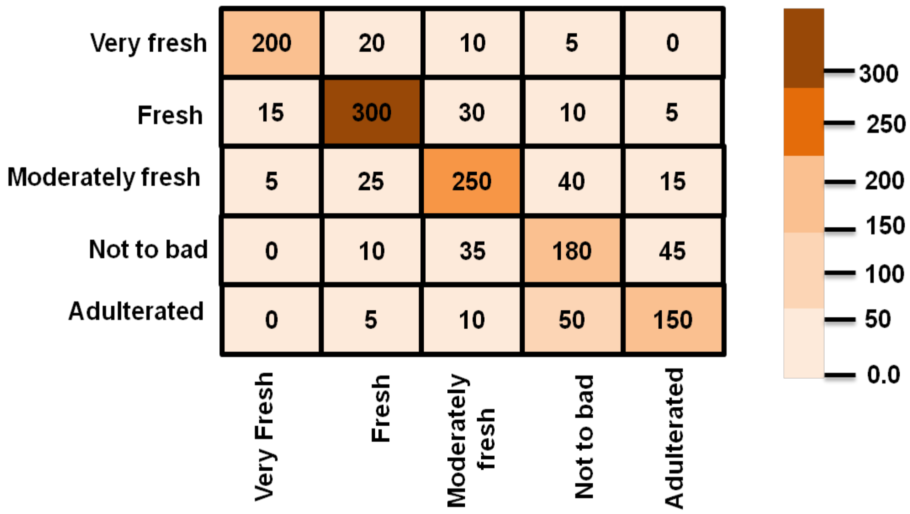

Figure 2. Confusion matrix

Table 1. Comparative outcomes of proposed and existing methods

Methods	Sensitivity	Accuracy	Specificity	Precision
SVM[19]	86,03	90,42	95,00	94,86
RF[19]	83,40	85,47	87,50	88,47
PLS-DA[19]	86,03	79,20	71,46	81,11
1D-SE-ResNet[19]	90,77	93,72	96,25	96,06
DCRF [Proposed]	91,90	94,16	97,54	97,48

Accuracy: accuracy is the percentage of a model's correct predictions among all of its forecasts. The suggested (DCRF) approach produced a superior 94,16 % accuracy, whereas the SVM acquired 90,42 % accuracy, the RF obtained 85,47 % accuracy, the PLS-DA acquired 79,20 % and the 1D-SE-ResNet displayed 93,72 % accuracy.

Sensitivity: the sensitivity of the method in recognizing genuine positive instances among all reported positives is referred to as sensitivity in the detection of meat freshness. When compared to more conventional approaches like SVM (86,03 %), RF (83,40 %), and PLS-DA (86,03 %), 1D-SE-ResNet (90,77 %) The suggested DCRF algorithm demonstrated superior performance, achieving a sensitivity of 91,90 %.

Specificity: the percentage of real negatives that a model properly identifies out of all actual negatives is known as specificity. The proposed DCRF (97,54 %) acquired a high specificity by outperforming comparable approaches like SVM (95 %), RF (87,50 %), PLS-DA (71,46 %), and 1D-SE-ResNet (96,25 %).

Precision: precision can be defined as the proportion of accurately anticipated instances that were positive to all cases that the algorithm projected as positive. The suggested approach produced a superior 97,48 % precision value whereas the SVM acquired 94,86 %, the RF obtained 88,47 % accuracy, PLS-DA acquired 81,11 % and the 1D-SE-ResNet displayed 96,06 %. Figure 3 shows the outcomes of specificity, sensitivity, accuracy and precision values of proposed and existing methods.

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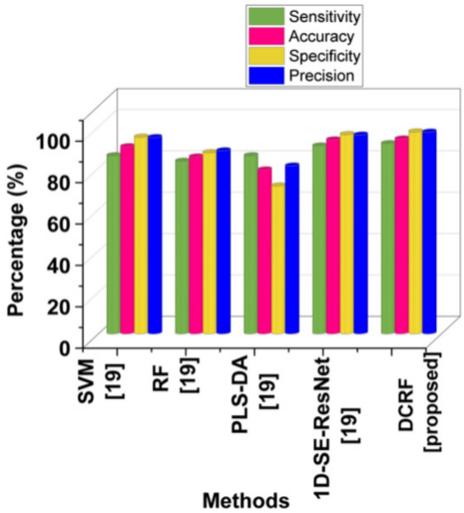

Figure 3. Comparative outcomes of proposed and existing method

Table 2 displays the comparision outcomes for the proposed and existing methods SVR, RFR, BPNN, 1DCNN, and 1DCNN-RER models.

Table 2. Evaluation of MAE, RMSE and R^2			
Methods	**MAE**	**RMSE**	**R2**
SVR[20]	4,1394	5,7176	0,9183
RFR[20]	2,9732	3,3293	0,9290
BPNN[20]	2,6486	4,6663	0,9456
1DCNN[20]	2,0250	2,4301	0,9852
1DCNN-RFR[20]	0,4619	0,9491	0,9977
DCRF [Proposed]	0,3196	0,9564	0,9991

MAE: it measures the average error magnitude that exists between the expected and actual data. The suggested technique DCRF obtains a 0,3196, while the results of Support Vector Regression (SVR),[20] RF Regression (RFR),[20] Back propagation Neural Network (BPNN),[20] 1-Dimensional Convolutional Neural Network (1DCNN)[20] and (1DCNN-RFR)[20] were only 4,1394, 2,9732, 2,6486, 2,0250 and 0,4619, respectively.

RMSE: the measure is the standard size of the variations between the experimental and anticipated values. In contrast to other current approaches like SVR (5,7176), RFR (3,3293), BPNN (4,6663), 1DCNN (2,4301) and 1DCNN-RFR (0,9491) our suggested DCRF approach produced better outcomes with 0,9564 RMSE.

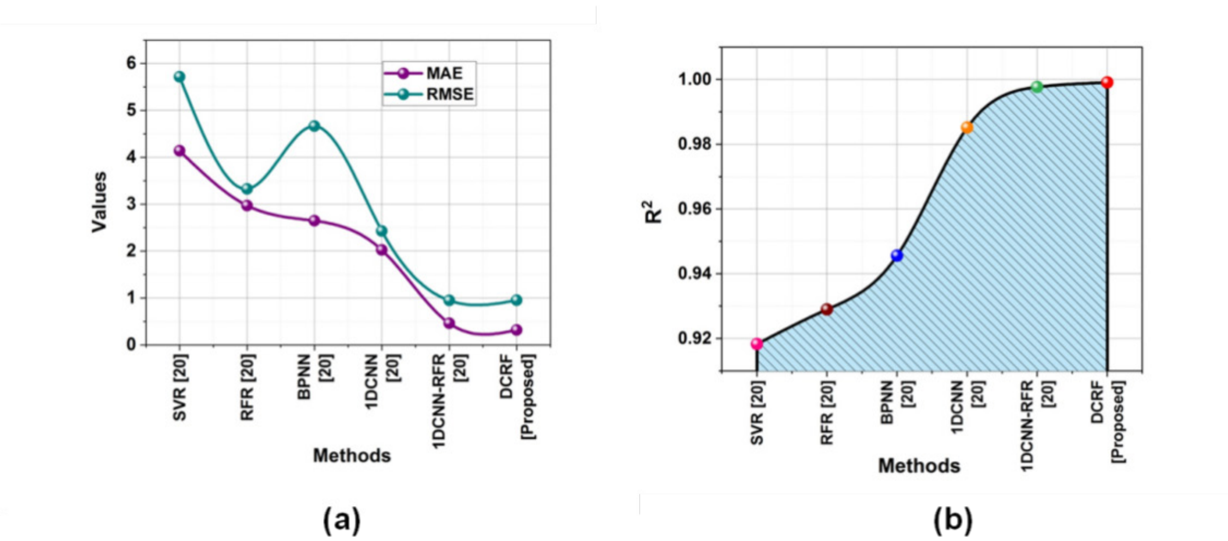

Figure 4. Outcomes of (a) RMSE, MAE and (b) R2

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R2: an indicator of the extent to which variability in a regression model's dependent variable may be predicted based on the independent variables is the degree of determination or R2. The proposed DCRF (0,9991) acquired a high coefficient by outperforming comparable approaches like SVR of 0,9183, RFR of 0,9290, BPNN of 0,9456, and 1DCNN of 0,9852 and 1DCNN-RFR of 0,9977. Figure 4 (a) debits the RMSE and MAE outcomes. Figure 4 (b) shows the outcomes of R2 values.

DISCUSSION

In this investigation, we discussed several existing methods, SVM and RF have inferior accuracy and sensitivity. PLS-DA is less predictable as it operates seriously with regard to of accuracy and specificity. Even with its strong performance, 1D-SE-ResNet is still not as good as more recent methods.In each significant efficiency indication, DCRF performed superior to these conventional methods. This implies that DCRF surpasses other techniques in correctly categorizing both fresh and decomposing meat, boosting overall meat categorization dependability. The potential of DCRF to offer highly precise estimations, substantially reducing oversights and enhancing prediction accuracy, therefore overcoming the deficiencies of existing approaches. DCRF indicates substantial improvements over previous procedures, delivering an effective solution for meat freshness and type identification.

CONCLUSIONS

Developing a contemporary method to help the meat business handle the meat offered in the market is the main aim of this project. The quality of meat has been a persistent issue since it's one of the main foods that people eat daily. As evidenced by the accuracy (94,16), precision (97,48), sensitivity (91,90), specificity (97,54), and the evaluation of regression are RMSE (0,9564), R2 (0,9991) and MAE (0,3196) reported in this study, the findings of the performance evaluation show how well the DCRF analyses TFI. Furthermore, the study illustrated how machine learning methods could help resolve problems and obstacles associated with data collection and availability. To provide a more accurate and realistic simulation, existing models may be merged with other ML techniques or altered in response to changes in meat freshness and type.

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