Hybrid Approach of CNN and SVM for Shrimp Freshness Diagnosis in Aquaculture Monitoring System using IoT based Learning Support System

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Abstract

Intelligent monitoring and spoilage detection of meat products is one of the most efficient approach which ensures that the food is consumed when it is fresh and avoids health hazards. Shrimp is most popular in terms of nutrition and exquisite nature. Shrimp has its own biochemical components like protein, carbohydrate, lipid and amino acids. However, the quality and freshness of shrimp is hindered in the post-harvested phase due to storage, handling and processing. The objective of this work is to propose an IoT- enabled real time vision-based support system for diagnosis of shrimp freshness, which is capable of performing assessment of quality and freshness using effective deep learning framework based on convolutional neural networks (CNN) and Support Vector Machine (SVM). The proposed model was measured with metrics such as precision, accuracy, F1 score which is respectively compared with the classical model (CNN with SoftMax) respectively. The comparisons shows that the hybrid model achieves 96.2% which is better than the classic model 94.7%. Based on this, it is observed that hybrid model using CNN and SVM found to be a better approach, which makes a difference to decrease the quality misfortune and help in advancement of criticism framework in industry 4.0.

Keywords: Convolutional neural network (CNN), Deep learning (DL), Shrimp freshness diagnosis, Support vector machine (SVM)

1 Introduction

Aquatic products are becoming highly consumable with good economic value due to rapid development of healthy eating habits. Among all marine foods, Around the world, Shrimp is considered as main factor of high-end famous dishes across various countries. Shrimp is wealthy in different microelements and vitamins conjointly have more restorative values which makes a difference for the treatment of skin ulcers, breast bruises, neurasthenia etc., Shrimp as a regular and territorial sea-going item, is inclined to weakening in quality amid capacity and carriage owing to the effect of microbes and related substances. The precise indicators related to the freshness of the shrimp during the storage stage includes odor, color, toughness, excretions, flesh. Generally, the fresh shrimp will not smell bad at all. When the freshness reduces it smell bad and the texture changes accordingly. The change within the shrimp quality influences the eatable esteem and weakens safety, so it isn't simple to store, and the brief rack life truly influences the deals and circulation of the items [1]. Thus, it is exceptionally imperative to decide the freshness and rack life of shrimp in opportune and precise way which helps the consumers and Industry to avoid health hazards and food wastage. Shrimp is one of the most popular aquatic products among people worldwide as it has unique characteristics in terms of taste and exquisite nature. Shrimp is highly perishable food and contains fundamental nutrients like easily digestible proteins, fats and vitamins [2]. As the human living standards changes rapidly, the quality of shrimp becomes a necessary factor valued by the consumers. The quality and freshness of shrimp is hindered in the post-harvested phase due to storage, handling and processing [3]. This significant problem is caused by various environmental changes like temperature, pressure, odor, color and texture cause a change in the chemical properties [4]. Freshness is considered as a vital calculate of shrimp quality for coordinate utilization by customers or as a crude fabric for industry by makers. The quality and freshness of shrimp is hindered in the post-harvested phase as it is tiny and elastic in structure and hence it is really challenging task to monitor the freshness variation of shrimp instantly. In order to meet the necessity of utilization rate and high-quality requesting, shrimps must be prepared in effective and healthy way. Sometimes to increase the productivity, producers may use chemical processing over the product to keep it always fresh and consuming this may impose health risks [5]. Normal consumers find it difficult to identify whether the shrimp is fresh or not. Thus, a simple, reliable, low cost, expeditious, and accurate monitoring system is becoming more essential and imperative to estimate the quality of shrimp freshness. To reduce the loss and man power, Farmers are largely dependent on cognitive solutions with technological developments. Benefits of smart monitoring using IoT improves farming industry in different ways wherein smart sensors ae used with less cost for collecting tons of data, provides better control over the internal processes [6]. Automating this analysis is more beneficial when the expert knowledge and decision support is not available readily.

At present, traditional way to analyze the freshness of the shrimp is widely used. It involves human intervention who will have direct contact to shrimp sample and analyze the

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quality based on the visual inspection [7] and odor assessment. Assessment by human intervention is difficult to be measured due to inconsistent, error prone, expensive and labor-intensive measurement for routine quality application. Later different well-established methods and techniques are introduced for monitoring the freshness of shrimp such as sensory evaluation method [8], biochemical methods, chemical methods, image processing techniques and other freshness indices. All these techniques are having its own advantages and disadvantages in which the sensory evaluation is highly sensitivity and good selectivity [9-10]. However, the sensor-based output is not accurate as it is influenced by instrument and external environment like temperature and humidity and also causes decision eccentricities due to weakness and subjectivity [11]. Standalone techniques for shrimp freshness are already available and in use [12]. Though these standalone techniques are beneficial, a single platform with real time vision-based technique will be more efficient and considerably create good impact for next generation quality monitoring solution.

2 Related Works

Research on deep learning algorithm has confirmed and verified that combining CNN for feature extraction [13-14] and SVM for classifier has shown outperforming output for classification. This motivated and inspired us to design a hybrid model for Shrimp freshness diagnosis. This work aims to design a hybrid approach of CNN-SVM model capable for giving quantitative output in real time with the prediction of shrimp quality in terms of freshness index and remaining shelf life of shrimp.

Rahman et al. [15], expressed an approach uses excitation emission matrix with charge coupled Camera for assessment of frozen seafood freshness. In this work, the shrimp sample is taken and cooled for on ice and stored at 60 degrees Celsius. The frozen shrimp were analyzed for ATP mixtures and potential of hydrogen by means of a fiber optic supported fluorescence spectrophotometer. Chemical investigation of solidified shrimp uncovered that K-value and PH esteem expanded. K-value visualization was at that point approved successfully with diverse super chilling strategy and the forecast precision was 95% and 5% is of estimated root mean square error under cross validation.

Khodanazary [16], presented a model designed to create a Quality Index Method for ice stored shrimp during twelve days of storage analyzing periodically. This model used partial least square regression to correlate quality index method attributes, linear regression analysis to check the storage time and chemical and bacteriological quality parameters were interpreted using principal component analysis. For each quality attributes the scores were given ranging from 0 to 3. By connecting the output with biological and physicochemical modifications that happened is examined based on QIM. To compare the average value, analysis of variance is identified and applied. The QI which is being calculated expressed the association in sequential manner when compared to the capacity time which in turn might be utilized to survey the left-over capacity time to an exactness of ±1 day. The rack life of ice-stored Metapenaeus affinis consenting to bacteriological, physicochemical comes approximately of QIM is 9 days' time span in which it is good for use.

Taheri-Garavand et al. [17], presented a combined effect of ozone innovation with altered air bundling procedure to make strides the quality and increase shelf life of shrimp. The samples are taken pre-treated using ozonated water and chlorinated water. For every specific day (third day) samples were taken for the analyses. Ozonated water taken after by Adjusted barometrical bundling expanded the shelf life and kept up the satisfactory sensorial traits, guarantees low microbial tallies and at last protected the chemical parameters.

Yu et al. [18], elucidated a method uses the concept of hyperspectral imaging, along with deep learning-based algorithm is applied for discerning the shrimp quality during cold storage. The captured images acted as samples which are then categorized into two sets and is named as new and stale. Based on stacked auto-encoders (SAEs) based deep learning algorithm the phantom features were hauled out from the HSI data later those features are taken as input form to classify the freshness grade of shrimp. To do classification, logistic regression (LR)-based deep learning algorithm is applied over the data. In order to visualize the freshness grade through classification map, an image processing algorithm have been developed. Finally, in the result shown very clearly the rapid and non-destructive detecting freshness grade of shrimp with the combination of hyperspectral imaging technique and deep learning algorithm.

Feng et al. [19] expressed a work under cold storage conditions in which changes in quality features and freshness parameters are evaluated using IoT enabled monitoring system and electronic nose spoilage detection system. The determined features like texture, color, sensory and pH value are taken for analysis which were measured and evaluated at different temperatures. Principal component analysis is used to gather and combine sensory information to find the similarities and relationship between the data. The freshness level of samples is clustered using convolutional neural networks and support vector machine-based algorithm. The dataset is taken for analysis by dividing the samples into training and testing data. The accuracy rate of training and testing data is compared to detect the freshness and quality of the sample salmon fish. By this work, it is observed that the accuracy rate is shown as expected by using CNN-SVM algorithm which might aid to decrease quality loss during cold storage.

Ye et al. [20] present a study in which a hyper spectral imaging system collectively with the different spectral processing techniques were adopted to identify the freshness of shrimp. The demonstrate is totally based on the three pre-processing strategies such as Savitzky-Golay to begin with subsidiary, multivariate scramble adjustment, and standard ordinary variate, three wavelength calculation to dissect the characteristics such as arbitrary calculation, uninformative factors disposal and competitive versatile reweighted inspecting, and four discriminant models such as fractional slightest squares separation examination, slightest squares bolster vector machine, irregular timberland, and extraordinary learning machine were utilized. After comparing all the strategies and calculation, the model produced finest solution based on SNV-CARS-ELM also distinguished as the ideal demonstrate for freshness detection of shrimps.

3 Materials and Methods

3.1 Proposed System

The proposed architecture represented in Figure 1 shows detailed information about hybrid model deployment in offline mode and validating the model using real time vision-based system. The basic flows start from image data sets which is then divided into testing and training data sets. The features of images are extracted using CNN, which is then passed into SVM as input for classification. Training and validation are done and the model is deployed for real time testing using the system hardware.

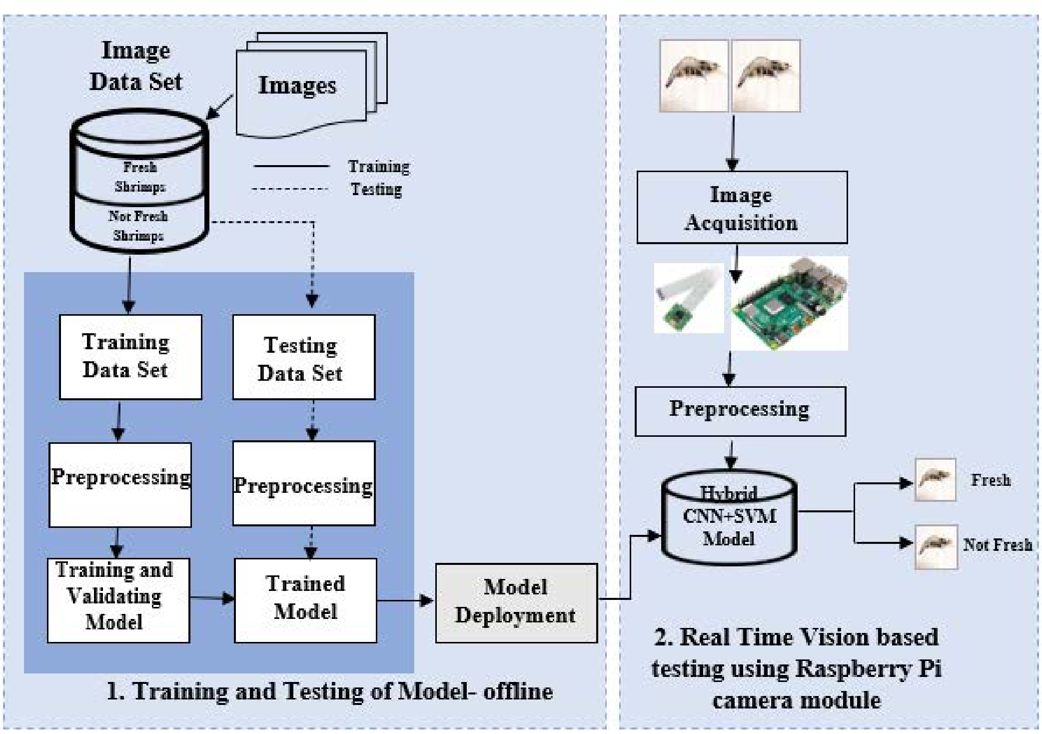

Figure 1. Architecture of proposed system

3.2 System Hardware

In the proposed work, for real time testing a 3D printed IoT chamber is designed. The distance, thickness and tallness of the chamber is properly constructed with clear measurement. The prototype consists of hardware components like Raspberry Pi Zero accelerated with vision boater for neural network inference, Pi Camera and a 3-inch TFT LCD display module. In addition, two sensors (MQ3, TGS2602) have been connected in the system to collect the sensor data which will be used to investigate the quality of shrimp at different time intervals based on the odor. The hardware components used in the system were shown in Figure 2. This work is mainly proposed for detecting the freshness of shrimp by integrating sensors and computer vision methods to caricaturist human biosensing abilities.

3.3 Image Acquisition and Data Collection

In order to develop the real-time visual inspection system for freshness diagnosis, deep learning models were trained and tested using the data sets collected manually. The details of the data sets, image pre-processing and training/testing of the models are described below.

3.3.1 Shrimp Sample Preparation

Shrimp (Litopenaeus Vannamei) samples are freshly purchased from a sea food market in Chennai district, Tamil Nadu. While purchasing the shrimp, approximately the weighted average of shrimp is calculated which is nearer to 15.00 ± 0.05g per shrimp. Once after it was purchased, immediately all shrimps were washed using clean cold water. After draining, shrimp samples are kept in refrigerator with ideal temperature of 4 degree Celsius in a container made of plastic which had depleted gaps. Shrimp samples were taken and tested every day for a total of 5 days.

After testing, the samples are kept back in refrigerator daily to maintain the same ratio. Figure 3 shows the original image of shrimp sample taken on first day of testing. Table 1 elucidates the input parameters considered for data samples.

Figure 2. Proposed system hardware

Figure 3. Sample shrimp image (Litopenaeus vannamei)

Table 1. Input parameters considered for data collection

Parameter	Values
Size of the image	384×256 or 256×384
zoom	No
Mode	No Flash
Sensitivity	200-ISO
Aperture ratio	f/4.5
Resolution	600 dpi minimum
Mode	Manual
Image data type	jpg

Color and advent are two primary components choosing the showcase acceptableness of meat items. Whereas destroyed shrimps appear to be misty, a new shrimp is glowing. The outer skin of shrimp looks polishing with layer of watery and clear visually initially when the shrimp is fresh [21].

Afterwards, it continually turns out to be melancholy and stained (which is reddish in color) due to expanded contagious growth. All these improvements have made it possible to apply image process methods for classification of freshness, and the hybrid CNN and SVM model was proposed in this work to define the differences between the images obtained and classify them.

3.3.2 Data Sets

Initially the data sets are collected manually at different time intervals to perform training, testing and validation of deep learning models both classic and hybrid. The datasets are categorized in to two classes based on the time span from the day of purchase of the sample: fresh shrimp (days 1–3) which is of 300 images, and spoiled shrimp (days 4-5) which is of 200 images based on the appearance as defined in Figure 4. Thus, the data sets had totally 500 images (i.e., 5*100 images), which was then converted into 5,044 images after performing data augmentation method which is mentioned in section 3.3.4.

These data sets are further divided for training, validation and testing using five-fold cross validation mechanism which is discussed in Section 4.1, certainly for training and testing purpose for both classic and hybrid model.

The horizontal and vertical distance is appropriately fixed over the chamber to avoid external disturbances. The samples are placed in the chamber and the images were taken every day and the of capturing images is done for a period of five days as defined in Figure 4. Once after capturing the image the samples are placed back into the refrigerator every day. The position of the chamber, sample, sensor and camera is same throughout the test. While taking the images through Pi camera for testing purpose, the environment lighting conditions are maintained properly to ensure the test samples are taken with proper distribution of light for accurate testing.

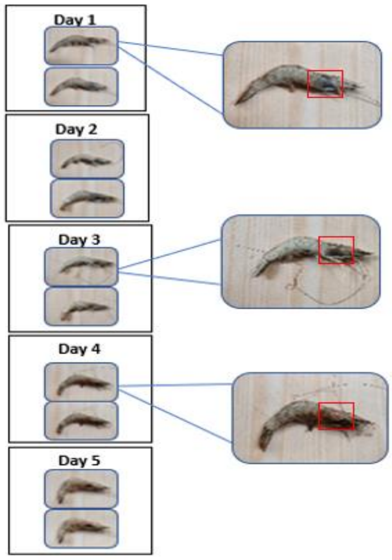

Figure 4. Appearance variations of shrimps

3.4 Parameter Measurement of Shrimp

3.4.1 Odor Related Shrimp Freshness Measurement

A gas sensor array is used to gather parameters related to odor for determining shrimp freshness. The retort of the sensor is pulled out as an attribute. During the experiment, the sensor which is placed inside the chamber was sealed properly to get steady and dependable estimation. After each experiment the chamber is cleaned properly before the start of next experiment. The odor of shrimp is measured using metal oxide semiconductor gas sensor. The sensor used in this experiment Is TGS2602 which has sensitivity characteristics to measure ammonia, Volatile organic compounds and hydrogen sulphide. The detection range varies from 1 to 30 parts per million. The odor parameter changes are determined by the sensitivity response of the gas sensor used in the chamber which in turn shows the wide range of changes in the output. The feature measurement of odor is calculated using principal component analysis algorithm. By determining the TAN content (Total Ammonia and nitrogen) the freshness of the shrimp is measured. According to the shrimp freshness standard if the ammonia level is less than 13 mg L-1, then the shrimp is fresh and if the ammonia level is greater than 13 mg L-1, then the shrimp is not fresh. So, based on the PCA analysis, the proposed work helps in finding changes in the shrimp odor. Table 2. represents the relationship between shrimp freshness and TVB-N.

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Table 2. Shrimp freshness and TVB-N relationship

Shrimp Freshness	TVB -N (mg)
Fresh	Less than 15
Spoiled	15 and More

3.4.2 Computer Vision based Shrimp Freshness Measurement

The image datasets are labelled with different names according to the type of class. As this proposed work uses convolutional deep neural network, huge volume of data is required for the network to improve the training stage for gaining knowledge on the weights and factors. Exceptionally expansive number of information is required for the network to move forward the preparing stage for learning the weights and variables. To reach higher execution, data augmentation strategy is applied to extend the training data with same name and minor mutilation is added to the images. Totally diverse techniques beside turn, tallness move, measurement move, zoom, flat flip and shear concentrated were associated in the midst of this work for growing the preparing dataset.

As there is a dataset imbalance, image augmentation technique is performed by applying rotations, vertical and horizontal turns. This is basically done to practically balance the two classes which finally obtained 2540 fresh images and 2504 spoiled images.

After augmentation, these images were normalized which in turn divided the pixel of the image by the value 225. So as to obtain each pixel with value between 0 and 1 for improving the learning process at faster rate. The size of the original image is converted into 224 × 224 pixels and then fed into the model.

The model proposed in this work is mainly for classification of shrimp freshness, which is majorly composed of three steps: Image pre-processing, feature extraction and classification. In pre-processing, the data set is being arranged and ordered to feed as input to the neural network to be trained efficiently.

3.4.2.1 Feature Extraction

Once the image data are read and preprocessed, the model which is depicted in Figure 5 is implemented. In this work, VGGNET architecture is applied as it shown higher performance compared with other algorithm [22] especially in image processing application.

VGGNET consists of various blocks mid which the input of each block remains as yield for the past blocks. It succeeds in building a convolution of 16 to 19 profound layers Neural systems by stacking 3 ∗ 3 convolution parts.

The central layers of CNN are Convolution that are made as channels (bit) which performs linear mathematical operation for removing subordinate focuses of intrigued in the input image [23]. The Pooling layer is dependable for diminishing the spatial measure of the Convolved Highlight. Usually, to diminish the computational control required to handle the information through dimensionality lessening. Besides, it is valuable for extricating prevailing highlights which are rotational and positional invariant, hence keeping up the method of viably preparing of the show. In the architecture of the network in between the convolution layer, the pooling layer has been added to control the overfitting.

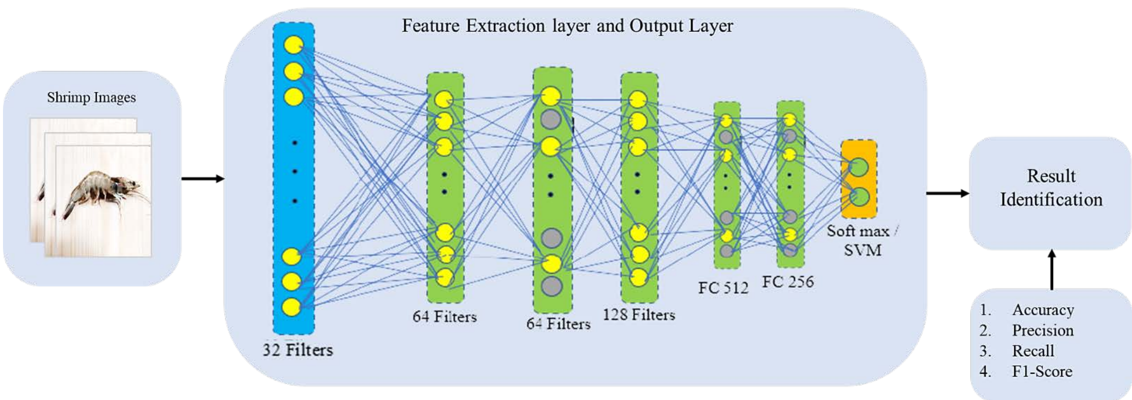

Figure 5. Classifier model for training and testing phase

A colossal run of variables, huge preparing information and expensive estimations are needed for neural network learning. In order to provide optimal solution for proper learning by the network, pre-trained network is taken as an important factor for feature extraction. The network model which has been trained are connected for extricating particular highlights which may be a central perception and after that these highlights are graded off by a modern classifier. As the model follows linear preconnected path, each procured picture of shrimp is modelled based on the real weights which has been assigned randomly which basically makes the network get trained for better classification. By performing this operation, the images are categorized in to two classes based on the time span from the day of purchase of the sample: fresh shrimp (days 1–3), spoiled shrimp (days 4-5).

In proposed model, the size of the original images is 384×256 or 256×384 which is converted to 224×224 pixels as input size and then fed to the CNN model. The data goes through the below mentioned layers in hybrid model which is then converted into different sizes leading to extraction of features.

The input image for feature extraction passes through four convolution layers of the kernel size of the 3x3 filter and four layers of the maximum pool using the 2x2 filter used to identify the freshness of the shrimp. To perform classification, output of the convolution layer will pass through a fully connected layer consisting of 512 neurons and 256 neurons and consisting of two dense layers, and finally reaches a dense layer with two neurons. increase. The latter uses SVM with linear sum of slack variables which is commonly referred as L1-SVM and a linear activation.

The original image is resized into 224x224x3 images (200x200 pixel image with color channels of 3) and fed through the convolution layers, where the convolution operation is carried out the input image and the predefined filter or kernel to obtain the feature map:

Here, the convolution operation is performed using two functions f and g, which in turn written as f*g. The integral transform is done for the two functions with one shifted and reversed is performed by using the formula (1).

$$x(m) = (f * g)(m) = \int_{-\infty}^{\infty} f(x)g(t-x)dx \qquad \textbf{(1)}$$

The variables x, f, g and m represent the following:

Function f is the image fed as input to the convolution layer

Function g represents the filter

Variable m is the displacement

Function x is the feature map

Convolution operation is done as linear fashion with four layers, in which the first layer is of 32 feature maps with kernel size as 3x3 with same padding and the ReLU function is applied as activation function to increase the non-linearity. This layer is followed by a maximum pooling layer with pool size as 2x2 and a dropout of 0.2. This is further followed by batch normalization to avoid overfitting in the model.

The second layer and third layer are with 64 filters with kernel size of 3x3 ReLU activation function each with its respective 2x2 max pooling layer and also followed by a dropout of 0.2. Figure 6 shows the algorithm for convolution phase. Finally, the fourth layer is the final convolution layer with 128 filters with a 3x3 kernel size with the ReLU activation function followed by a last 2x2 max pooling layer to which a 0.2 dropout is applied. The end of the convolution operation contains flattening layer to flatten the output as one-dimensional vector.

The activation function used in the model is ReLU function. In each layer of convolution, ReLU function (Rectified Linear Unit) is used as the activation function [24]. Basically, it is applied in each layer for the purpose of doing mathematical operation on each entry and its function is defined by the following formula (2).

$$f(x) = \begin{Bmatrix} 0 \; for \; x < 0 \\ x \; for \; x \geq 0 \end{Bmatrix} \qquad \textbf{(2)}$$

The pooling layer is added to reduce the image size by maintaining the features of the image. In the next layers, the feature filter size is increased to make the model to learn the features of the image to get better accuracy. After that the image flattened to convert the image from two dimensional values to one dimensional value.

After convolution layer, image classification and retrieval are done in different ways one is using classic model and other is with hybrid model.

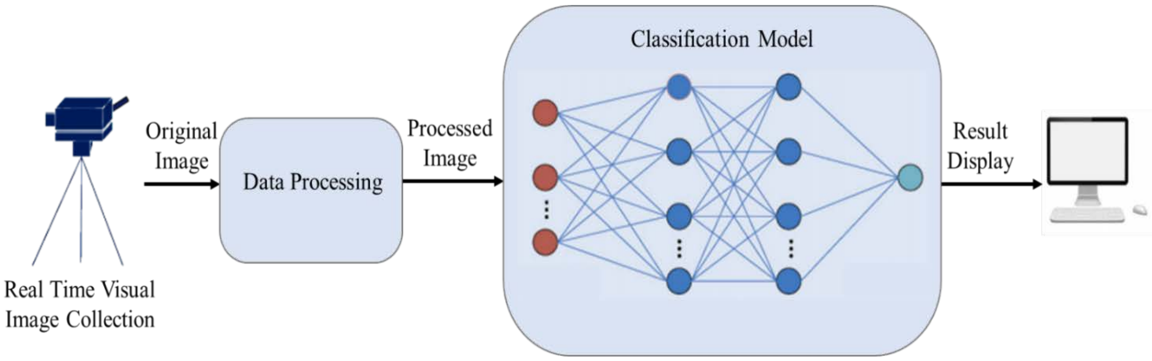

Figure 6. Running phase of the system

3.4.2.2 Classification using Classic Model

In classic model, after convolution layers, two fully connected layers of 512 and 256 neurons and a dropout of 0.2 is used. After these two layers, a last layer is used which is fully connected layer with only 2 neurons as the classification is binary. In this layer, Soft max activation function is used, which is defined by using the formula (3).

$$\sigma(Z)i = \frac{e^{Zi}}{\sum_{j=1}^{K} e^{Zj}} \qquad \textbf{(3)}$$

The variables zi, K represents the following Function g represents the filter

zi represents the last layer output

Variable K represents the number of classes(binary)

After applying soft max function, model is compiled using model. compile() method with loss function as cross entropy using formula (4).

$$CE = -\sum_{t}^{i} ti \log(si) \qquad \textbf{(4)}$$

The variables C, ti, si represents the following:
ti log(si) represents expected label and score for class
Variable C represents the number of classes to classify

3.4.2.3 Classification using Hybrid Model CNN and SVM

In Hybrid model, after convolution layers, two fully connected layers of 512 and 256 neurons and a dropout of 0.2 is used. After these two layers, a last layer is used which is fully connected layer with only 2 neurons as the classification is binary.

Then the linear activation function is used, which its output is proportional to the input received, and in this work, the input is the output of the last layer. To perform the classification in the final layer, we have implemented the SVM classifier. The SVM can be a directed learning calculation that operates on hidden space based on the separation of classes using planes or hyper-planes. The multidimensional data is classified into respective categories using SVM method by acquiring the optimum boundaries or hyper-planes.

SVM classifier have been implemented in the final layer for classification. For loss function, L1-SVM standard have been used which performs linear sum of slack variables using the formula (5).

$$\min \frac{1}{p}\ w^T w + C \sum_{i=1}^{p} \max\left(0, 1 - y'_i (w^T x_i + b)\right) \quad \textbf{(5)}$$

The notations C, y', $w^T x$, b, $w^T w$ represent the following

C represents an arbitrary value or hyperparameter setting value which is penalty parameter.

y' represents real label of shrimp

$w^T x$+ b represents the predictive function

$w^T w$ represents L1 standard which defines the Manhattan standard

The SVM strategy for classifying the freshness of the shrimp sample will minimizes the basic risk, not at all like classical calculations that work by minimizing the size of the observational error or the moment power of the error. By using nonlinear bits, it is also capable of forming nonlinear choices. The selection of the correct parts for the SVM was motivated to prevail over other direct approaches to decision-making.

4 Experimental Results and Discussions

4.1 Results and Evaluation- Computer Vision Analysis

In this work, two different models have been designed, one is classic model (CNN with SoftMax) and the other one is hybrid model (CNN +SVM). Both these models ae evaluated in two phases: In first phase the models were tested in off-line mode on a holdout test set with 10% of images from data set and in the second phase, as the datasets are relatively small in size, the models were tested by taking data from the real time system in which cross validation was used for evaluating the performance of the model.

The configuration applied for both models are presented in the Table 3.

Table 3. Configurations applied for training

Model / Configurations	CNN + Soft max	CNN + SVM
Epochs	140	140
Batch Size	32	32
Optimizer	Adam	Adam
Activation function	Soft max	Linear
Loss function	Cross entropy	L1-SVM

In first phase, evaluation for training is done with 4,035 images from the total images and validation is done with 505 images, where the training accuracy and losses are evaluated. For both Classic model and Hybrid model is then evaluated using 504 testing data to calculate the metrics such as precision, accuracy, recall and F1-score with confusion matrix. The recognition effect is measured as accuracy. The precision is used to measure the model precision. The recall rate of the model is measured which gives the probability that the model is correctly classified in to the corresponding class.

The F1-score is the average of precision and recall for measuring the performance of the model defined by the formula such as (6) – (9). Figure 7 represents the confusion matrix of Classic model with 255 True Positives (TP), 223 True Negatives (TN), 15 False Negatives (FN) and 11 False Positives (FP). Figure 8 represents the confusion matrix of Classic model with 258 True Positives (TP), 227 True Negatives (TN), 11 False Negatives (FN) and 8 False Positives (FP).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \textbf{(6)}$$

$$Precision = \frac{TP}{TP+FP} \quad \textbf{(7)}$$

$$Recall = \frac{TP}{TP+FN} \quad \textbf{(8)}$$

$$F1 - Score = \frac{2*Precision*Recall}{Precision+Recall} \quad \textbf{(9)}$$

Based on the metrics retrieved, the comparison of classic model and Hybrid model on hold out test set is shown in Table 4 and Table 5. Table 6 shows comparisons between classic and hybrid model, in which hybrid model shows remarkable performance in the metrics. At the outset, the hybrid model is able to achieve better performance and accuracy in classifying the shrimp freshness.

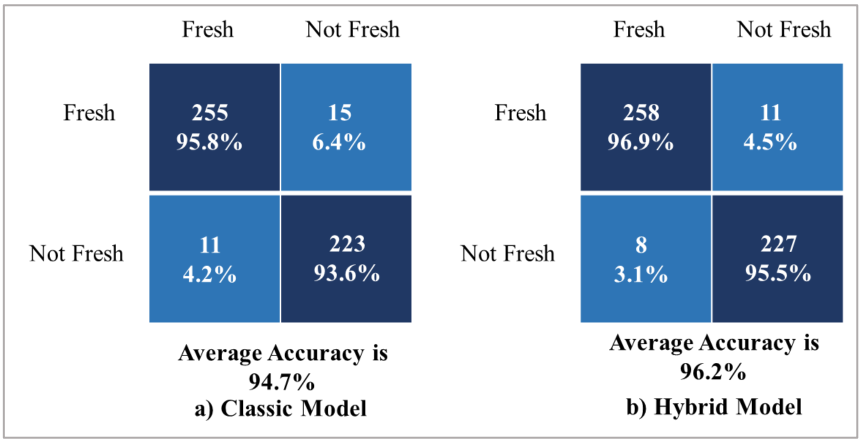

Figure 7. Confusion matrix

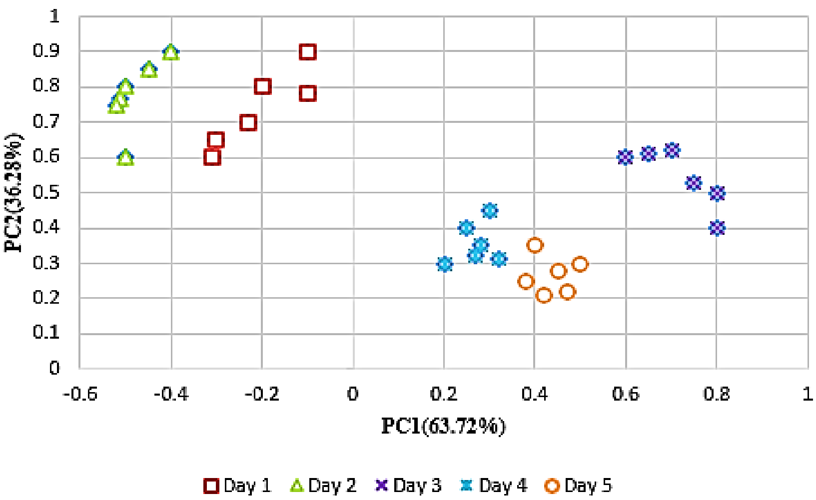

Figure 8. Principal component analysis result

Table 4. Metrics of classic model

Class/ Metrics	Accuracy	Recall	F1-Score
Fresh	95.8%	96.1%	94.4%
NotFresh	93.6%	93.2%	95.1%
Average	94.7%	94.6%	94.7%

Table 5. Metrics of hybrid CNN and SVM model

Class/ Metrics	Accuracy	Recall	F1-Score
Fresh	96.9%	96.7%	96.2%
NotFresh	95.5%	95.6%	96.1%
Average	96.2%	96.21%	96.20%

Table 6. Metrics of classic and hybrid model

Model / Metrics	Accuracy	Recall	F1-Score	Precision
Classic	94.7%	94.6%	94.7%	94.7%
Hybrid	96.2%	96.21%	96.20%	96.2%

4.2 Results and Evaluation- Sensory Analysis

As a supporting component we used sensory data for analyzing the freshness level of shrimp based on the odor. The data which we collect through sensors may have more than two-dimensional information, so we performed principal component analysis in order to interpret the data obtained by measurement of the volatile gases from the decomposed shrimp using MQ3 and TGS2602 sensors. The results of these analyses are summarized in Figure 8. The first principal component is displayed as the abscissa, while the second principal component is plotted as the ordinate. The samples were divided into groups based on Figure, from which the diurnal deterioration of the shrimp could be determined. It was hypothesized that utilizing the signal from the sensors, the diurnal deterioration of fish might be discovered using the principal component analysis approach.

4.3 Discussion

The trained models are further evaluated by using real time vision system. We used a collection of 30 images consisting of 15 fresh images and 15 stale images. In this phase, as the data set is relatively small, a five-fold cross validation was applied to generate classification results for images. This cross validation was used in the output layer for evaluating the linear classifiers and an average of five iterations were performed over shrimp data set. It is observed that the precision obtained for both models are satisfying in five-fold cross validation results for classification, which are summarized and compared with metrics in Table 7.

Table 7. Metrics of classic model and hybrid model

Model / Metrics	Accuracy	Recall	F1-Score	Precision
Classic	90.7%	90.6%	90.2%	90.7%
Hybrid	93.2%	93.3%	92.9%	93.2%

Even with real time system, the proposed hybrid model indicates better superiority in classifying shrimp freshness compared with classic model. The precision of both models is shown in the Figure 8 for fresh and not fresh shrimps when tested in offline phase and real time phase. The Hybrid model is further deployed in IBM Watson [25] Visual recognition environment, which produced accuracy of 92% with threshold value of 0.5 which similar to the accuracy measured in real time system. Figure 9 represents the classification accuracy based on visual recognition. However, the performance differs for offline test set and actual real-time testing samples, which might be due to the different data collection environment.

Figure 9. Classification accuracy in IBM Watson

5 Conclusions

In this work, we proposed a hybrid CNN-SVM model for shrimp freshness diagnosis classification. The hybrid model was developed using the shrimp datasets collected which was then trained, validated and tested in different phases. The hybrid model demonstrated high classification performance than the classic model. There is nearly 2% of improvement in all the metrics which indicates that this hybrid model is reliable and effective to be used for classifying shrimp freshness. This proposed work helps in reducing the quality loss and aid in development of feedback system in industry 4.0 to take further measures to avoid health hazards and food wastage. In future, it can also be used in fashionable nutritional related organization, smart findings of freshness and not just within the cultivation trade. The findings obtained can also be used in the future to create mobile apps so that consumers can only check the freshness of the shrimp by taking a snapshot of the shrimp.

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