

Optimizing micro cold storage for detecting stale food and fruits

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Abstract. Cold storage are a critical element of the food supply and sustainability supply chain for preservation and maintaining the quality as well as the nutritional value of stored items. This work investigates into the adoption of Artificial Intelligence (AI) techniques in cold storage with the aim of reducing food wastage thereby contributing to SDG-2. This work presents an algorithm based on the Inception v3 AI model that aids in assessing the condition or quality of fruits and vegetables that are stored in controlled environmental conditions. From the proposed model, one can identify with an accuracy of 99%, the correct condition of the fruit/vegetable. Additionally, other structures have demonstrated high accuracy, such as the compact Convolutional Neural Network (CNN) achieving 98.54% precision and the sequential model with 98% precision, both of which significantly contribute to the robustness of the results. These high accuracy rates praise the effectiveness of AI in categorizing farm products. Depending on the freshness level, the commodities are classified as fresh and rotten. Classification of such market offers the farmers very crucial information that allows them to make the right decisions, on the right time to sell their produce hence achieve stability of market price. This research not only helps to apply AI into the cold storage systems but also assist in helping the farmers through data-driven decision-making. The feature of recognizing the freshness of stored products proves the opportunities in applying the AI in managing inventory in cold storage and creating efficient and sustainable system. Finally, this work represents a great progress towards the development of smart systems improving the quality of products and a viable economics of storing them in the common granaries of farming industries.

Keywords: Freshness, Classification, Fruit, Inception v3, AI for food preservation.

Acronyms

AI	Artificial Intelligence
SDG	Sustainable Development Goals
CNN	Convolutional Neural Network
AIML	Artificial Intelligence and Machine Learning
IoT	Internet of Things
SVM	Support Vector Machine
FPGA	Field Programmable Gate Arrays
LSTM	Long Short Term Memory
ANN	Artificial Neural Network
ARIMA	Auto Regressive Integrated Moving Average
WSN	Wireless Sensor Network
RMSE	Root Mean Square Error
MLPANN	Multilayer Perceptron Artificial Neural Network
ReLU	Rectified Linear Unit
MAE	Mean Absolute Error
Hu	Haugh unit

TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative

1 Introduction

Fruits and vegetables, historically, have been included in our dietary guidelines for their health-promoting properties as they are rich in vitamins, minerals, and antioxidants. Most horticulture varieties are produced across the country due to its vast geographical features, however the extent of loss in this sector is put at 35–40% of production according to the Indian Council for Agricultural Research due to respiration, water loss, and cell softening throughout the post-harvest with negative impact on its quality and shelf life [1]. This necessitates the development of low-temperature, high relative humidity storage facilities as per the guidelines provided by the National Horticulture Board of India [2], displayed in Table 1, to help safeguard perishable

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Table 1. Grouping of fruit and vegetables as per National Horticulture Board of India.

Groups	Temperature range (0 °C)	Relative humidity (%)	Examples
1	0–2	90–95	Apples, mushrooms, beets
2	0–2	95–100	Cabbage, carrots, spinach
3	0–2	65–75	Garlic, dry onions
4	4.5	90–95	Lemon, oranges, lychees
5	10	85–90	Beans, okra, eggplant
6	13–15	85–90	Banana, papaya, mango
7	18–21	85–90	Sweet potatoes, watermelons, yam

goods, extend their shelf-life, and ensure their year-round availability to consumers. The operational challenges and complexities of maintaining cold storage at optimal conditions, while also minimizing energy consumption and reducing food wastage, present formidable tasks. A micro-cold storage, a developing concept with a maximum storage capacity of half a ton of produce, is a specialized storage unit, designed to be used at the farm-gate level to help small farmers and local vegetable vendors, owing to existing large and infeasible storage options [3, 4].

Additionally, the incorporation of Artificial Intelligence (AI), both on-farm and post-harvest, has the potential to revolutionize cold storage management through temperature and humidity regulation and optimum energy usage, leading to well-organized inventory management. This would help farmers store, identify, and sell the appropriate produce to the market and convert their efforts into financial gain. AI technologies, such as machine learning and predictive analytics, have demonstrated their ability to adapt and improve various aspects of the supply chain. A multidisciplinary approach integrating cold storage technology with image analytics would aid in continuous monitoring of the quality of the fruit or vegetable guaranteeing minimum nutritional degradation. This research paper, thus delves into the synergy between cold storage and AI, exploring the opportunities for enhanced performance and sustainability by developing an algorithm through the Inception v3 AI model which will help to identify the state or quality of the product stored to streamline inventory handling. The study evaluates the model performance in terms of its accuracy, precision, F1 score, and recall ability, while also comparing the parameters with the general sequential Convolutional Neural Network (CNN) model based on the review of literature carried out.

2 Literature review

food technology, micro-cold storage is an upcoming field wherein various aspects involving techno-economical parameters along with solar and thermal storage technologies have been the focus of study [5–10]. In the current work, technology enhancement is intended through, its integration with Artificial Intelligence and Machine Learning (AIML). Several AI-based approaches have been studied from cold room remote monitoring to fruit maturity assessment. This investigation seamlessly combined

machine learning with the Internet of Things (IoT) for the real-time monitoring of temperature, humidity, and carbon dioxide concentration. The data collected was subjected to experiments using varieties of algorithms which included; Support Vector Machine (SVM), Decision Tree, AdaBoost, and Gradient Boosting. In particular, it was found that the accuracy of the SVM algorithm was the highest and reached the level of 88%. Such integration of various technologies opens up the possibility of hugely improving the real-time monitoring capacity relevant for applications that are time-sensitive and for which accurate data is critical [11]. In another study, a decision tree algorithm of supervised machine learning was used to control the temperature and the humidity for the preservation of crops through smart warehousing [12]. An FPGA-based food spoilage detection system was designed using methane gas and moisture content of stored food as data recorded to the YoloV5 machine learning model shown in [13]. The hyperspectral imaging technology was applied in the case of identification of chilling injuries and other quality features in horticulture and food products as well as monitors for internal disorders [14]. Additional studies carried out on integrating AI with horticulture preservation are elaborated in Table 2.

The study as shown in Table 2 indicates the various AI methodologies used in the Food and Storage industry. Inception v3 model is a recent inclusion under CNN which has been explored for face shape classification [23], health care for pulmonary image classification [24], and also in ancient architecture detection [25]. However, its application in the food storage industry is yet to be explored. This study, hence proposes to integrate the inception v3 model with the cold storage technology for the detection of the quality of horticulture produce. Image analytics have been used to identify fruits such as apples, oranges, and bananas by classifying their color images for the state of freshness (fresh/rotten) to predict their shelf life and useability. The subsequent section elaborates on the methodology of the current work.

3 Methodology

The classification of fresh fruits and rotten fruits is done in this work. The dataset used for this work consisted of images of apples, bananas, and oranges belonging to the fresh and rotten categories [26]. The main objective of the

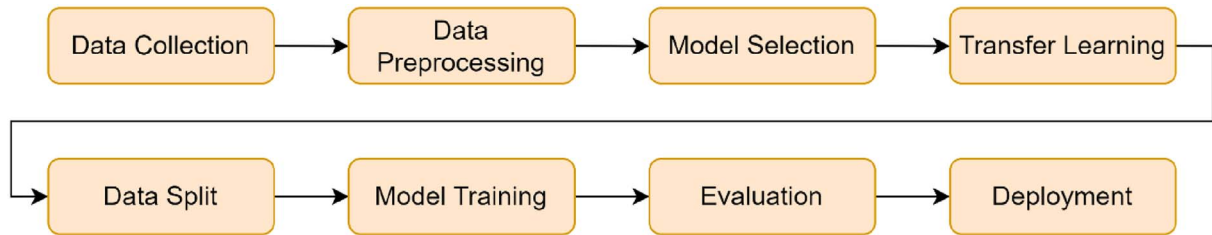
Table 2. Literature review on various AI methodologies in food technology.

Reference	AI methodology	Observations	Remarks
Loisel <i>et al.</i> [15]	Neural networks	This paper discusses the definitions, challenges, and machine learning methods for detecting breaks, highlighting issues and data sources for training models.	Wireless temperature sensors and data transmission giving real-time temperature analysis will enable automatic warning and determination of time-temperature threshold along with break classification.
Hoang <i>et al.</i> [16]	Convolutional LSTM model	Implementing demand response requires precision to safeguard food quality and safety. Four Artificial Neural Network (ANN) models, leveraging deep-learning techniques, were devised to anticipate temperature and power demand fluctuations in cold storage resulting from Demand Response applications.	Four deep learning models were developed, including traditional LSTM, stacked LSTM, bidirectional LSTM, and convolutional LSTM. Results show that ANNs can predict product and air temperature evolutions during demand response periods.
Khanuja <i>et al.</i> [17]	Auto-Regressive Integrated Moving Average (ARIMA)	This paper suggests a framework that leverages IoT, Cloud Computing, Machine Learning, and Big Data Analytics to transform the cold transport industry, guaranteeing the preservation of freshness and quality.	The IoTs revolutionizes fleet management by utilizing Big Data and Machine Learning to interpret and compute data from sensors. Future work aims to enhance complex protocols for enhanced features in small network scenarios.
Kim <i>et al.</i> [18]	CNN-LSTM	This study proposes a deep learning-based Haugh Unit (HU) prediction model to monitor egg quality in cold chain storage and transportation. The model uses non-destructively measured weight loss to determine egg freshness.	Leveraging weight loss data alone, the target transfer learning CNN-LSTM demonstrated a significant reduction in RMSE, decreasing from 6.62 to 2.02 compared to a random forest regressor. Furthermore, the application of data augmentation techniques resulted in a noteworthy decrease in the Mean Absolute Error (MAE) of HU prediction for the target model, dropping from 3.16 to 1.39.
Gao and Xu [19]	IoT	This paper presents a Wireless Sensor Network (WSN) for monitoring fruit cold storage using the ZigBee protocol. The system uses a Chip CC2430 for information processing and wireless node detection.	The system offers advantages such as automatic data acquisition, storage, and remote control for storage managers.
Feng <i>et al.</i> [20]	SVM	This study introduces a system that enhances transparency and trust by collecting and validating quality parameters. Employing K-means and SVM algorithms enables effective classification and prediction of quality loss.	The training set and test set proportions, falling within an allowable deviation range, stand at 88.89% and 87.17%, respectively. Utilizing the SVM model, the Root Mean Square Error (RMSE) for the training set is 0.1502, while for the test set, it is 0.1793. Notably, both the K-means and SVM models exhibit superior accuracy in their performance.

(Continued on next page)

Table 2. (Continued)

Reference	AI methodology	Observations	Remarks
Pan <i>et al.</i> [21]	MultiLayer Perception Artificial Neural Network (MLPANN)	This paper proposes a hyperspectral imaging system to detect chill damage in peaches stored in cold storage. The system used an ANN model with eight optimal wavelengths.	Post-harvest storage-induced changes in factors such as firmness, soluble solids content, extractable juice, titratable acidity, and chlorophyll content were identified. ANNs pinpointed eight optimal wavelengths, achieving classification accuracies of 92.9%, 100%, and 95.8%. The MLPANN models demonstrated effective predictive performance for quality parameters.
Wagle <i>et al.</i> [22]	New compact CNN	This study introduced novel models, N1, N2, and N3, for plant leaf disease detection and assessed their classification accuracy and training efficiency in comparison to the AlexNet model. Notably, the proposed models exhibit a more compact design and require reduced training time compared to AlexNet.	The envisaged model effectively identifies diseased plant leaves in mobile phone-captured images. Its compact design allows deployment as a standalone mobile app, offering farmers an efficient solution with commendable classification accuracy.
Wagle <i>et al.</i> [23]	Three-layer CNN	This work proposed compact CNN models that reduced computational complexity to detect tomato plant leaf disease detection when compared to the ResNet-101 model	The suggested method demonstrates enhanced performance, attaining classification accuracies of 99.13%, 99.51%, and 99.40% for N1, N2, and N3 models, respectively. These models are characterized by their compact size, increased efficiency, and reduced time complexity, marking a substantial stride in the effective management of infected plants.

**Fig. 1.** Methodology.

work was to sort the fruits into fresh or rotten categories of the fruit type. There are three varieties of fruits *viz*; apples, oranges and banana and further they are categorized as fresh or rotten fruit.

The stepwise methodology which has been used to develop this work is highlighted in Figure 1. The subsequent operations are undergone for the distinction between fresh and rotten fruits and the type of fruits which can be apple, orange, and banana.

Data collection: Firstly, collect a large set of pictures of different fruits and vegetables in their fresh state as well

as in the state when they rot. Transparency of data and its applicability in the real world depend on it, as well as on proper balance. It is therefore equally important to label each photo that is taken as being fresh or rotting.

Data preprocessing: In the process of working with datasets introducing to the machine learning algorithms, data preprocessing is a very important step and this is valid, especially when working with image datasets for classification. The ImageDataGenerator class in the Keras module is used in the augmentation of the image data which helps to add more variation to images helping the model to

generalize. Cropping, rotation, and shifting of the images in the dataset were done using ImageDataGenerator. Rotation assists the model to learn different orientations of the object, zooming helps in exploring different scales, shifts assist the model to learn about different positions and flipping is useful in the training of mirror images. These random transformations make the model less sensitive to variations what can be seen in real-world data. This process allows for the exclusion of noise and the requirement of the model to function well with new data it has never seen before.

Model selection: While deciding on the base model for the classification problem, Inception v3 was selected. Some of the strengths of the deep CNN Inception v3 include the fact that it is able to obtain delicate features from photographs, and also it has achieved satisfying results in image recognition experiments.

Transfer learning: Use Transfer Learning by first loading or introducing a big data set like ImageNet in order to load the Inception v3 model with some pre-trained weightage. The model is allowed to adapt to the sort of work one is doing by unfreezing the subsequent layers while keeping the initial layers' weights frozen.

Data split: The training set is used to train the model; the tuning of the hyperparameters is facilitated by the use of the validation set; while the final evaluation of the initialized model is done via the use of the test set.

Model training: The choice of an optimizer is appropriate in this case with Adam and cross-entropy as the chosen loss function, proceed to train the Inception v3 model on the training dataset. There always is a risk of overfitting; the next advice is to monitor the model's performance on the test/validation set and the use of early stopping is highly recommended.

Evaluation: The metrics to be calculated for assessing the model's effectiveness in differentiating fresh and rotting produce include accuracy, precision, recall, and F1 Score with the same computations being executed on the test dataset once training is complete.

Deployment: If the model performs somewhat acceptably, plug it into a web or mobile application where a user can simply take pictures of fruits and vegetables to check their freshness.

The dataset comprises high-quality/color photos of fruits in a natural setting on different backgrounds and under different lighting conditions. The associated fruit type – banana, apple, or orange, and their freshness status – fresh or rotten are written beside each of the images. The sample data for fresh fruit and rotten fruits are depicted in Figure 2. The distribution of the data is done to guarantee that the model can effectively learn to distinguish between the two freshness classes, the dataset should contain an approximately balanced distribution of images of both fresh and rotten fruit. The images are annotated based on the name of the fruit and its freshness type as fresh or rotten. The classification models are trained and assessed using these labels. The dataset is split into two subsets: a test set, which is used to assess the model's performance, and a training set, which is used to train the classification model. The images used for training the model are 10,901 and 2,698 images are test images.

The images in the dataset could be in different states of freshness – from fully fresh to slightly rotten. Developing a model that can distinguish between these freshness levels with accuracy is a challenge. This dataset is useful for creating machine-learning models that will aid in automating fruit quality control in the food sector. It can be applied to grading and sorting procedures to enhance product quality and decrease food waste.

3.1 Neural networks

Neural networks are a class of machine-learning models inspired by the human brain. They consist of interconnected nodes (neurons) organized in layers to process and learn from data. They are widely used in tasks like image recognition, natural language processing, and more, thanks to their ability to capture complex patterns and make predictions. A generalized structure of neural network is shown in Figure 3. Here in this work there are six output classes that are classified as fresh apple, fresh banana, fresh orange, rotten apple, rotten banana, and rotten orange.

3.1.1 Inception model

Within the Inception architecture family, Inception v3 is a potent CNN model intended for object recognition and image classification applications. Developed by Google Research, Inception v3 is a popular choice for a variety of computer vision applications due to its high performance and efficiency being the main features of Inception v3 and the reasons it is frequently chosen over competing image classification models. Three color channels (R, G, and B) and color images with a resolution of 224×224 pixels are input into the model's input layer. Usually, preprocessing is done on these photographs to make sure they are properly scaled and normalized. The model processes the input and the output layer providing the output as the encoding from the six classes (fresh apples, fresh bananas, fresh oranges, rotten apples, rotten bananas, and rotten oranges). The architecture of Inception v3 model is shown in Figure 4.

3.1.1.1 Key components of the Inception v3 model

Inception modules: Utilizing Inception modules – blocks of layers that integrate various convolution types – is a defining feature of Inception v3. These modules include max-pooling functions along with 1×1 , 3×3 , and 5×5 convolution filters. The network can extract features at various levels of abstraction due to the combination of these filters. Furthermore, to reduce the dimension and control the cost, the researchers have also employed 1×1 convolutions.

Convolutional layers: The convolutional layers that are present in making of Inception v3 architectures are responsible for training and recognizing feature in input images. The use of filters of different sizes and strides is utilized in these layers in order to capture features at different scales.

Batch normalization: The activations of the network are scaled using batch normalization layers which helps in making the training more stable and convergent.

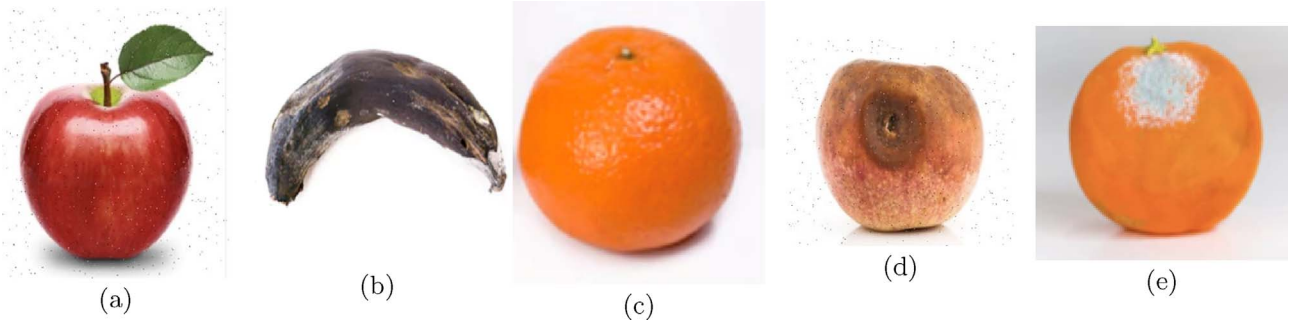


Fig. 2. Sample images of the dataset.

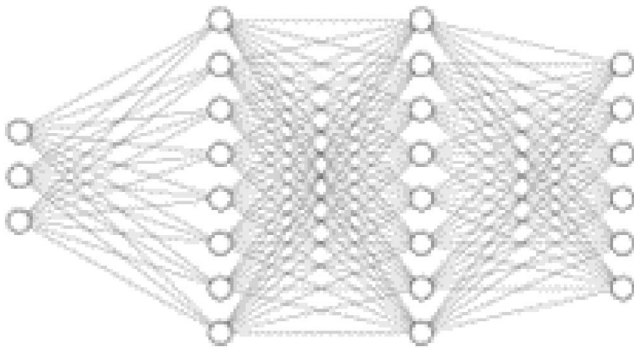


Fig. 3. General structure of a neural network.

Activation functions: Most of the time, Rectified Linear Unit (ReLU) activation functions are included in Inception v3 to introduce non-linearity.

Max-pooling layers: These layers enable the reduction of the size of the feature maps as much as possible while retaining only the most important information.

Fully connected layers: When the network at the end of Inception v3, there will be one or more fully connected layers used in classification tasks.

Reduction modules: It also includes reduction modules to reduce the network input image sizes for better computation practicality of the inception v3. These kinds of modules enable the network to capture not only spatial features but also semantic ones because they reduce the spatial dimensions of the feature maps deepening them as well.

Auxiliary classifiers: Inception v3, two auxiliary classifiers have been included and are placed at the middle level. The objective of these classifiers is to reduce the vanishing gradient issue during training. The instructive features are selected for better network performance.

Factorization: Reduction of a number of parameters is achieved by decomposition methods; this sharpens the computational proficiency of the network. For example, a 7×7 convolution could be implemented as two 3×3 convolutions; it is also possible to use two 5×5 convolutions. In this way, the number of parameters shrinks, and, thus, the network's ability to learn the hierarchy of features boosts.

Inception v3 over other models: Inception v3 has proved rather popular, firstly, because of its rather

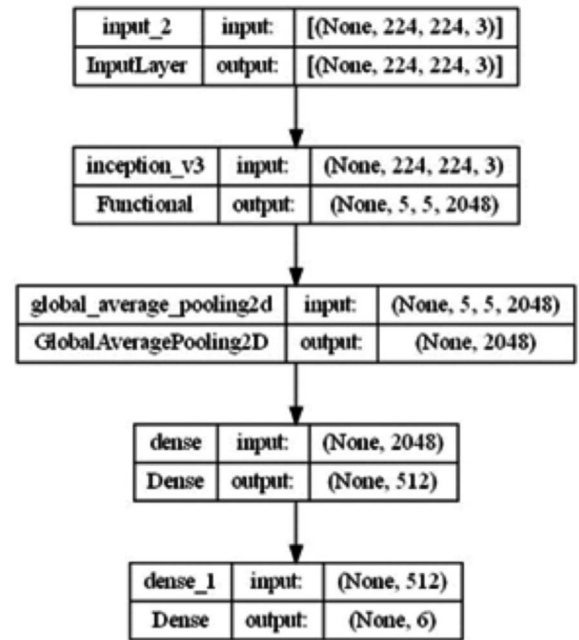


Fig. 4. Architecture of the model.

unconventional architecture and, secondly, due to a number of characteristics that benefit it compared to other models. Here are a few justifications for choosing Inception v3 over alternative models.

Architectural innovation: The concept that underlies the Inception modules, or parallel convolutions with different filter sizes is the notion of Inception v3. This innovation makes the model capable of capturing features that may include features at multiple and multi-level of abstraction. It leads to improved feature extraction and representation which is important in demanding image recognition exercises.

Efficiency: This has made Inception v3 preferred especially in tasks that entail some form of restriction concerning the usage of computational resources. In exchange for returning a good performance with parameters, it leverages several parallel convolutions and smaller filters that could ultimately lead to shorter training and inference time.

Robust performance: Compared with other approaches, Inception v3 has recently reached near

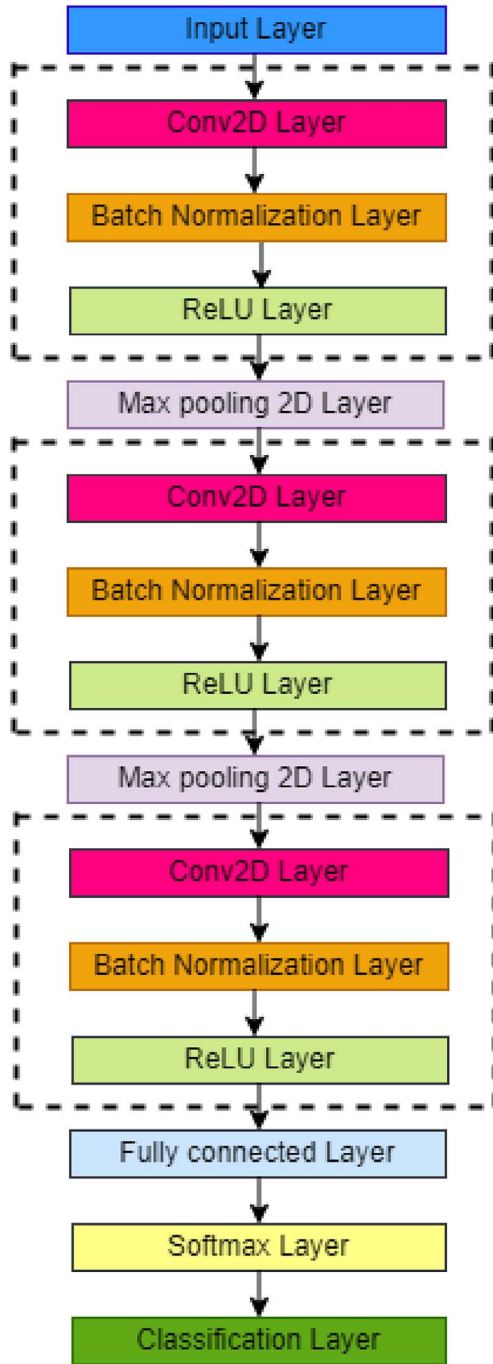


Fig. 5. Compact CNN model.

state-of-the-art performance on different image classification and object detection tasks. This makes it suitable for a wide range of computer vision applications due to its ability in enabling the detection of different features in an image and accommodate different sizes of objects.

Transfer learning: Many of the pre-trained features such as the features in the configuration Inception v3 are perfect for transfer learning. Analysing the features, which the model acquires by training on large datasets including

ImageNet, the model can be fine-tuned for a certain dataset. This is often the case where convergence occurs at a faster rate and superior performance on some task that is endemic to the domain is reported.

Decreased overfitting: By reducing the number of model parameters, Inception v3 and similar techniques such as the global average pooling make an effort at reducing overfitting. It is helpful when working with sparse data.

Auxiliary classifiers: Inception v3 is a deep network that has one of its auxiliaries placed at several network depths. These supplementary classifiers are of help in averting generation of uncontrolled outputs and in training the model. They can help control the passage of gradients during training, which is especially helpful in a context of deep networks.

Skip connections: The inception models have been also defined to incorporate the skip connections which are inspired by the ResNet. Functions such as improving gradient flow through these connections are especially beneficial to train very deep networks which will aid tasks that require the depth of models.

Community support: Being one of the most utilized models, Inception v3 has the strong backing of a number of users and a massive availability of resources for problem-solving and getting started.

Versatile applications: Inception v3 model is applied in several applications such as segmentation, detection, and classification. It is a good choice for a range of use cases that characterise many real-world applications because of this versatility and fairly good efficiency on these tasks. This is due to it has unique architecture, high performance, efficient and flexible for several computer vision applications. Inception v3 is optimal for managing the CPU and giving the best results when working on various domains such as object detection, image classification, and much more.

3.1.2 Sequential model

The sequential model mentioned previously was made of utilizing the CNN for the procedure of feature abstraction and the hierarchical pattern identification. It includes three convolutional layers in which all are connected with ReLU activation functions to identify non-linear correlation in the data. Between these convolutional layers, there are three max-pooling layers the pool size of which is (2, 2) shrinking the spatial size but preserving only the most significant features. Furthermore, three dropout layers in the rate of 0.2 has been added to the model to reduce overfitting by rendering a percentage of neurons randomly non-functional during training. The last part of the model architecture is consisted of two dense layers as it is the transition from convolutional features to the output. The dense layers have ReLU activation functions which enables the extraction of high level of abstracts from the learned feature. The last layer consists of a softmax layer to include probabilistic cues to the outputs of the model, thus useful for multi-class classification. This sequential model of using convolution layers, pooling layers and dense layers in succession is ideal for tackle tasks that involve spatial hierarchy in tuples as well

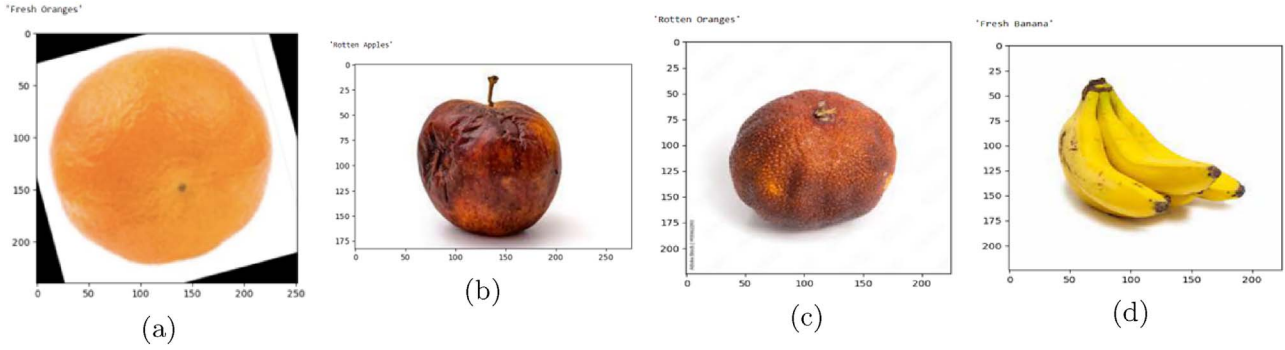


Fig. 6. Output images after classification.

Table 3. Confusion matrix for the classification of fresh and rotten fruits.

(a)

Confusion matrix of the test data with Inception v3 model

		Actual values					
		Fresh apples	Fresh banana	Fresh oranges	Rotten apples	Rotten banana	Rotten oranges
Predicted values	Fresh apples	392	0	1	2	0	0
	Fresh banana	0	381	0	0	0	0
	Fresh oranges	0	0	387	0	0	1
	Rotten apples	0	1	1	593	1	5
	Rotten banana	0	0	0	0	530	0
	Rotten oranges	0	0	1	3	1	398

(b)

Confusion matrix of the test data with sequential model

		Actual values					
		Fresh apples	Fresh banana	Fresh oranges	Rotten apples	Rotten banana	Rotten oranges
Predicted values	Fresh apples	521	0	1	0	8	0
	Fresh banana	0	324	60	0	1	3
	Fresh oranges	3	3	384	1	12	0
	Rotten apples	1	0	1	361	2	16
	Rotten banana	1	0	11	0	559	30
	Rotten oranges	0	0	0	0	0	395

(c)

Confusion matrix of the test data with compact CNN model

		Actual values					
		Fresh apples	Fresh banana	Fresh oranges	Rotten apples	Rotten banana	Rotten oranges
Predicted values	Fresh apples	384	2	2	7	0	0
	Fresh banana	0	377	0	1	3	0
	Fresh oranges	0	0	380	1	0	7
	Rotten apples	20	3	9	553	7	9
	Rotten banana	0	4	0	1	524	1
	Rotten oranges	1	0	19	18	3	362

as in extracting numerous features which is the case with image classification task.

3.1.3 Compact CNN model

The compact CNN model used in this work is shown in Figure 5. There are three sets of layers comprising of convolutional layer, batch normalization layer, and ReLU activation layer in the model. The first convolution layer is of size 3×3 with 8 filters. The second convolution layer is also of size 3×3 with 16 filters and the third convolutional layer used in this model is of size 3×3 with 32 filters. After each the convolutional layer is the batch normalization layer. Batch normalization employs a transformation to keep the mean output approximately centered around 0 and the output standard deviation close to 1. The ReLU activation layer is used after the batch normalization. The

maxpooling stride used in this model is 2. After the three sets of convolutional layers, Batch normalization and activation layer, the fully connected layer is used with the number of neurons same as the number of classification outputs. Softmax is used in the at the end of the classification model to output a probability distribution over the possible classes. This layer is responsible for prediction of the outcome. The classification layer shows the classified output to respective class.

Early stopping avoid overfitting: Overfitting happens when a model gets overly intricate and begins to fit the noise in the training set instead of identifying the underlying patterns in the data. As a result, there is poor generalization to new data, despite excellent performance on the training dataset. By terminating training as soon as the model's performance on a different validation dataset starts to deteriorate, early stopping helps avoid overfitting.

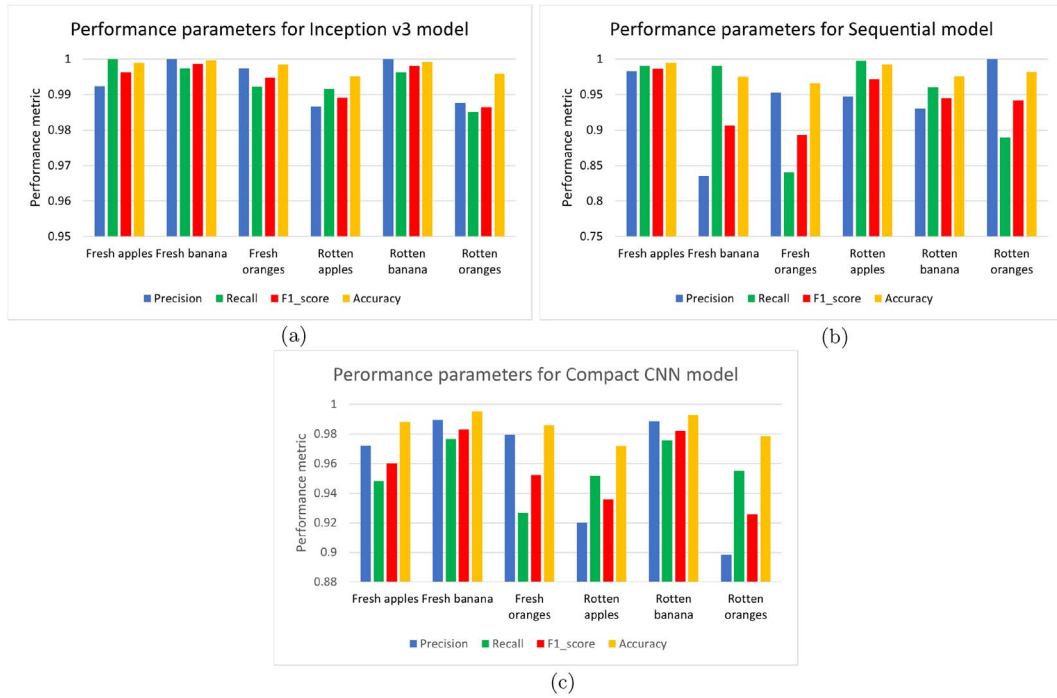


Fig. 7. Performance parameters evaluation for six classes. a) Performance parameters for Inception v3 model; b) Performance parameters for Sequential model; c) Performance parameters for compact CNN model.

Boost training efficiency: The training of deep learning models frequently takes a large amount of time and computing power. By ending training as soon as it becomes evident that more training is unlikely to improve validation performance, early stopping can save time and resources. This is extremely helpful when time or computational resources are limited. This is the general procedure for early stopping: The model's performance, such as validation loss or accuracy, is tracked during training at regular intervals. Overfitting of the model is indicated if its performance on the validation dataset begins to deteriorate (*e.g.*, validation loss increases or validation accuracy decreases). There is an early stopping point. At the point of early stopping, the training is stopped and the model weights are saved. Usually, this saved model is the one that performs better when applied to new data. Following this, the saved model can be used to forecast fresh data.

4 Results

This section provides a thorough rundown of the model's capabilities and performance. To help understand the fundamental architecture of our model, we start by presenting a graphic depiction of the network architecture. We then present the accuracy and loss graphs, which provide a concise depiction of the training and validation performance throughout epochs. We also explore a real-world classification scenario, showing how our approach efficiently classifies data and illuminating its usefulness. Together, these components offer a comprehensive picture of the model's functionality and possible use in practical settings.

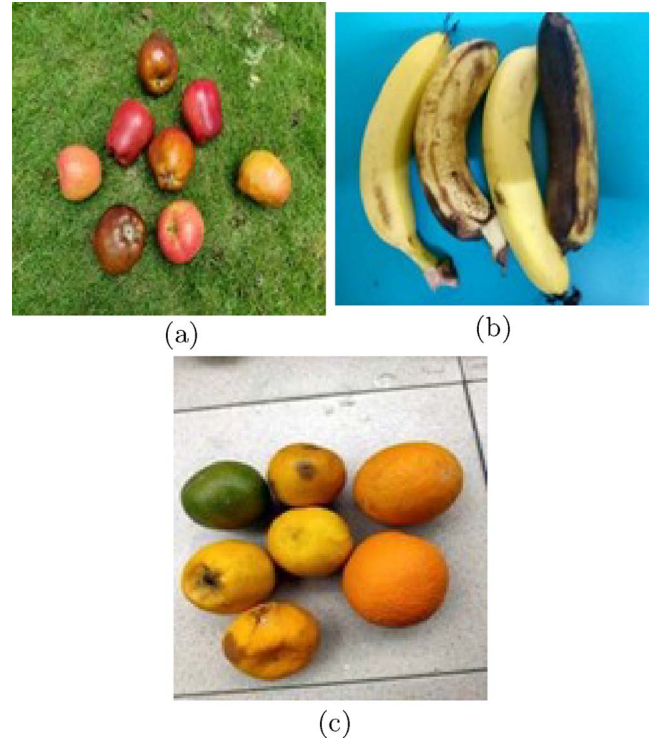


Fig. 8. Sample images of fresh and rotten fruits. a) Orange; b) Banana; c) Apple.

The classified output images are shown in Figure 6. The classified image in Figure 6a is of fresh orange, Figure 6b depicts rotten apple, Figure 6c shows rotten orange, and Figure 6d shows the fresh banana.

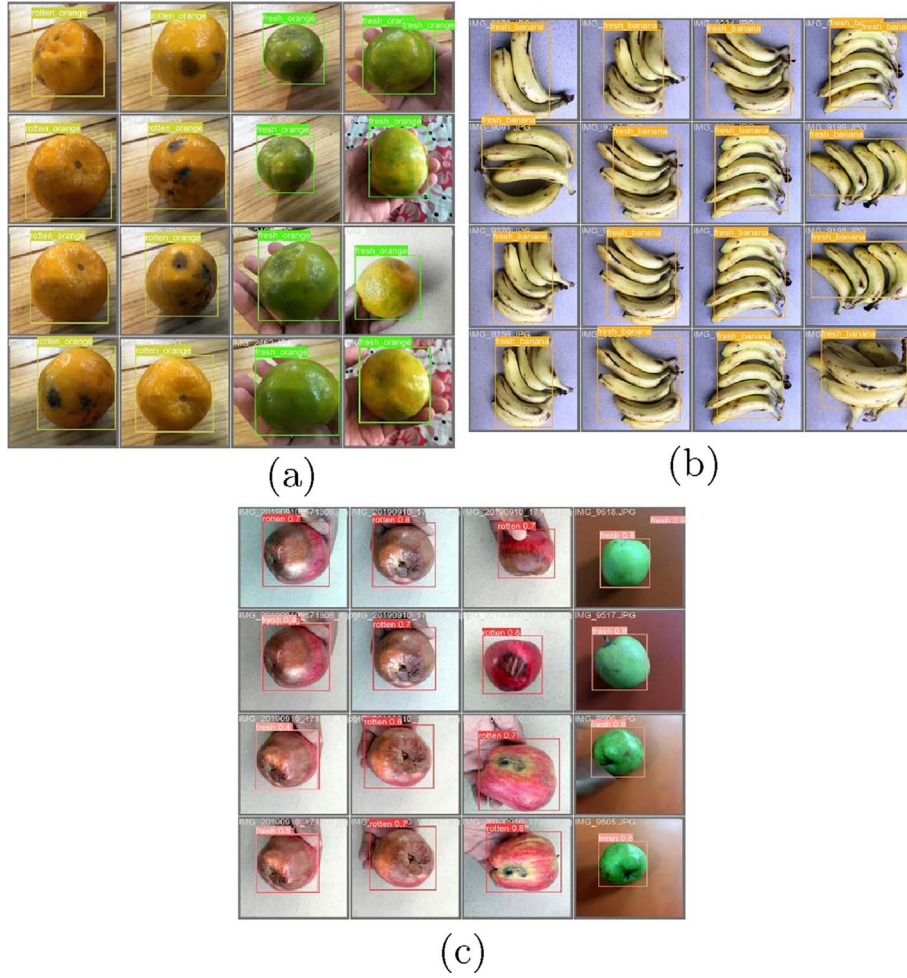


Fig. 9. Classified images of fresh and rotten fruits using YOLO v5 model. a) Orange; b) Banana; c) Apple.

The confusion matrix for the Inception v3 model, sequential model, and compact CNN model are as shown in Table 3a, Table 3b, and Table 3c, respectively. There are six classes, three for fresh fruits and three for rotten fruits like apple, banana, and orange. The diagonal elements of the confusion matrix shows the correct classification whereas, the non-diagonal elements of the matrix depicts the misclassification. The parameter *viz* true positive, true negative, false positive, and false negative can be evaluated from the confusion matrix. These values are further used to evaluate the performance metrics to analysis the performance of the models in the classification task.

The Accuracy, Precision, F1 score, and Recall are calculated using the equations illustrated through Equations (1), (2), (3), and (4), respectively. Where TP is True Positive, TN is True Negative, FP is False Positive, FN is False Negative

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

$$\text{F1Score} = \frac{2 \times \text{TP}}{2 \times \text{TP} + \text{FP} + \text{FN}} \quad (3)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (4)$$

The performance parameters of accuracy, precision, recall, and F1 score are evaluated for the Inception v3 model is shown in Figure 7a. The performance of the model for classification of fresh and rotten banana is better than other four classes. Figure 7b shows the performance parameters evaluation with sequential model. The performance is sequential model is less than the Inception v3 model. Figure 7c shows the performance metrics evaluation using compact CNN model.

5 Freshness of fruits

Classifying fresh and rotten fruits offers several significant advantages, particularly in industries such as agriculture, food retail, and supply chain management. The ‘FruitNet’ dataset [27] has been meticulously curated to address the challenges associated with fruit classification and

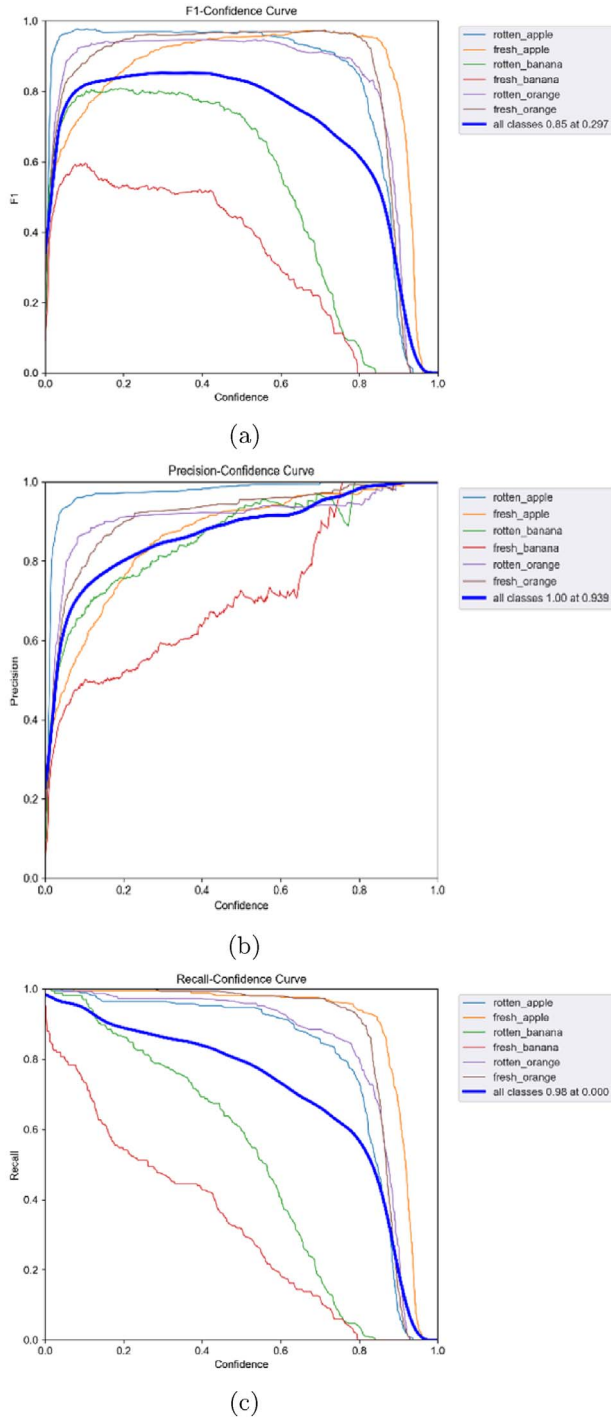


Fig. 10. The performance parameters of F1 score Precision and Recall. a) F1 Score; b) Precision; c) Recall.

recognition tasks, particularly within the context of Indian fruits. Recognizing the importance of high-quality image data for the development of robust machine learning models, this dataset offers a comprehensive collection of images across fruit classes: apple, banana, and orange images are selected for the study. The dataset consists of images of good-quality fruits, rotten varieties of fruits, and mixed-quality fruits – enabling nuanced analysis and

model training that can account for variations in fruit quality. The images were captured using a high-resolution mobile phone camera under diverse background settings and lighting conditions. The sample images of the mixed variety of fruits are shown in Figure 8.

It is essential to identify the fresh and rotten fruit and take necessary action to sort out the fresh fruits from the set of fruits as it will increase the shelf life of the fruit. The more ripened fruits can cause the other fruits to ripe due to the release of a plant hormone called ethylene [28]. Classification of the fresh fruit and rotten fruit is done using the YOLO v5 model. The classified output images are shown in Figure 9. Here each of the fruits gets classified with a label on it displaying the classification class of fresh or rotten and along with the percentage of classification.

The performance parameters of precision, recall, and F1 score are shown in Figure 10. Here in the graph, apple, banana, and orange are of fresh variety and rotten variety. The model is performing well with an F1 score of 0.85 at the specified threshold of 0.297. A precision score of 0.939 across all classes suggests that the model is making reliable predictions and is effective at minimizing incorrect classifications. Recall measures the proportion of actual positives that are correctly identified by the model.

6 Conclusion

Cold storages are widely used for bulk storage of fruits and vegetables so as to take care of seasonal variations in supply. Often, the stored commodities get rotten when left unmonitored for a long duration of time. This study reports the development of a classification model for segregating fresh and rotten fruits kept in a controlled environmental chamber. Such a model is useful to predict the condition of the stored fruits and the right time for them to be taken to the market. Classification algorithms like sequential model, compact CNN, Inception v3 and YOLO v5 were used in this study to predict the condition of the stored fruit in terms of its freshness. The Inception v3 model was found to be very accurate in classifying fresh and rotten fruits and therefore can render an invaluable tool in the management of cold storage conditions. The sequential, compact CNN and YOLO v5 gave an accuracy of 98%, 98.54%, and 90%, respectively. An efficiency of 99.78% is obtained for the Inception v3 classification algorithm in predicting the condition of perishable goods. Future work is focused on application of Inception v3 model into a prototype lab scale cold storage to determine the freshness of the products.

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Conflicts of interest

The authors declare no conflict of interest.

Author contribution statement

Shivali Amit Wagle: Conceptualization, Project Development, Writing, Review, and Editing. Prahas Nambiar: Data Curation and Analysis, Research Design and Methodology, writing draft. Sreelekha Arun: Data Curation and Analysis, Research Design and Methodology, writing draft. Pratham Panalkar: Data Curation and Analysis, Research Design and Methodology, writing draft. Prince Ekka: Data Curation and Analysis, Research Design and Methodology, writing draft. Vaibhav Kumar: Data Curation and Analysis, Research Design and Methodology, writing draft. Harsh Dhiman: Conceptualization, Project Development, Writing, Review, and Editing. Anindita Roy: Conceptualization, Project Development, Supervision, Writing, Review, Editing.

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