
Meat Freshness Prediction

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Github: <https://github.com/TheLohia/Phteven>

Dataset: <https://www.kaggle.com/datasets/vinayakshanawad/meat-freshness-image-dataset>

Abstract

In most retail stores, the number of days since initial processing is used as a proxy for estimating the freshness of perishable foods or freshness is assessed manually by an employee. While the former method can lead to wastage, as some fresh foods might get disposed after a fixed number of days, the latter can be time-consuming, expensive and impractical at scale. This project aims to propose a Machine Learning (ML) based approach that evaluates freshness of food based on live data. For the current scope, it only considers meat as a subject of analysis and attempts to classify pieces of meat as fresh, half-fresh or spoiled. Finally the model achieved an accuracy of above 90% and relatively high performance in terms of the cost of misclassification. It is expected that the technology will contribute to the optimization of the client's business operation, reducing the risk of selling defective or rotten products that can entail serious monetary, non-monetary and health-based consequences while also achieving higher corporate value as a sustainable company by reducing food wastage through timely sales and disposal.

the product's processing and display environment. In other words, when freshness is uniformly judged based on the number of days since initial processing, fresh food may be discounted or discarded, while spoiled products may still be displayed.

This project assumes a supermarket that sells fresh food including meat as the client and aims to create a system that evaluates freshness of meat based on actual meat conditions using images of meat as input. The system is expected to contribute to the optimization of the client's business by avoiding unnecessary discount or disposal, help it reduce the risk of damage caused by selling defective products, and improve its corporate value as a sustainable company if they can reduce food waste.

2. Assumption

This project sets some assumptions for the client's business operation and customers' behaviors.

- There are three classes in meat freshness: (1) Fresh (FS), (2) Half-fresh (HF), (3) Spoiled (SP)
- Meat will be treated based on its "predicted" freshness as follows: (1) FS: Sold for \$10, (2) HF: Sold for \$5 (discounted), (3) SP: Discarded
- The purchase probability of the meat depends on its "actual" freshness, which customer can tell based on its look, and price that is decided based on its "predicted" freshness. Actual FR has the purchase probability of 90% when sold for the original price of \$10. It will be purchased with 100% probability when sold for \$5, which is misclassification of actual FR being predicted as HF. The purchase probability of actual HF is just 10% when sold for \$10, which is a misclassification of actual HF being predicted as FR, because of its less appetizing look. If it is discounted to \$5 based on the correct prediction, the probability increases to 90%. For the same reason above, the purchase probability of actual SP is just 1% and 5% when sold for \$10 and \$5

1. Business Problem

Assessing the freshness of perishable food is a significant operational challenge for retailers, as it is time-consuming, and can affect their business performance as well as reputation if a wrong judgment is made. In most retail stores, the number of days since initial processing is used as a proxy for freshness. Regardless of actual freshness, products are judged to be fresh if fewer days have passed and stale if more days have passed. Products that have passed many days since their initial processing are discounted, and if they are still not purchased, they are ultimately disposed of. However, freshness is a dynamic factor that depends on

055 respectively, which are the results of misclassification.
 056 Table 1 shows the summary of purchase probabilities.
 057 The values in red indicate “misclassification”.

059
 060 **Table 1.** Purchase Probability of Each Actual|Price(Pred) Combi-
 061 nation

ACTUAL	\$10 (PRED AS FR)	\$5 (PRED AS HF)
FR	90%	100%
HF	10%	90%
SP	1%	5%

- 062
 063 • If meat is purchased, it will be consumed and thus if
 064 spoiled meat is purchased, the customer will have a
 065 health issue. A total cost of \$100,000 will be incurred
 066 due to legal action, reporting to health-related authori-
 067 ties, loss of corporate trust, and other related factors.

068 3. Methodology

069 This project experiments with two different models, namely
 070 ResNet and UNet to predict meat freshness, comparing their
 071 performance on a fixed set of metrics to identify the best
 072 performer. The original train dataset is split into train and
 073 validation dataset that are used for model development and
 074 hyperparameter tuning. The original validation set is treated
 075 as an ‘unseen’ test dataset that is only used for final model
 076 evaluation after all tuning has been done.

077 In evaluating model performance, a metric called MisClas-
 078 sification Cost (MCC), which is defined specifically for this
 079 project, is used. MCC is an expected value and represents
 080 the cost associated with misclassification, which depends
 081 on the actual class and the direction of the misclassification.
 082 A special metric apart from class based accuracy, precision,
 083 recall etc is required as the cost of misclassification is not
 084 symmetric, and hence certain misclassifications are more
 085 expensive or riskier than others.

086 MCC is calculated by *expected loss from misclassification*
 087 less *expected gain from misclassification*, which considers
 088 the probability of purchase in each case explained in 2. Assump-
 089 tion. Misclassification on actual SP samples leads to
 090 serious consequences due to customers’ potential health is-
 091 sue it could cause. Furthermore, “misclassifying actual SP
 092 as HF” has the higher expected cost than “misclassifying ac-
 093 tual SP as FR”. This is because discounts due to “predicted
 094 HF” can increase the purchase probability, which increases
 095 the risk. Thus, predicting actual SP as HF is considered the
 096 most costly misclassification that should be avoided in this
 097 project. Table 2 and 3 show MCC of each combination of
 098 actual and predicted classes and calculation of MCC.

099 **Table 2.** MCC of Each Actual|Pred Combination

ACTUAL PRED	CONSEQUENCE	MCC
FR FR	NOTHING(CORRECT)	\$0.0
FR HF	UNNECESSARY DISCOUNT	\$4.0
FR SP	UNNECESSARY DISPOSAL	\$9.0
HF HF	NOTHING(CORRECT)	\$0.0
HF FR	INEFFICIENT PRICING	\$3.5
HF SP	UNNECESSARY DISPOSAL	\$4.5
SP SP	NOTHING(CORRECT)	\$0.0
SP FR	COST OF \$100K IF PURCHASED	\$99.9
SP HF	COST OF \$100K IF PURCHASED	\$499.8

100 **Table 3.** Calculation of MCC

ACTUAL PRED	EXPECTED LOSS	EXPECTED GAIN
FR FR	\$0	\$0
FR HF	\$10*90%	\$5*100%
FR SP	\$10*90%	\$0
HF HF	\$0	\$0
HF FR	\$5*90%	\$10*10%
HF SP	\$5*90%	\$0
SP SP	\$0	\$0
SP FR	\$10,000*1%	\$10*1%
SP HF	\$10,000*5%	\$5*5%

101 An ideal model is one which minimizes the MCC. Hyperpar-
 102 ameter settings and corresponding total MCC are recorded
 103 in Weight and Biases in order to compare the performance
 104 of different models more easily. It has to be noted that the
 105 evaluation in this project highly depends on the assump-
 106 tions set in the previous section. In the real business setting,
 107 MCC must be modified following the user’s actual discount-
 108 ing policy, purchase probabilities and estimated cost of any
 109 consequences.

110 Simultaneously, to further enhance the model robustness,
 111 MCC was not used during training as an evaluation metric
 112 or the loss function. By doing this, the model is prevented
 113 from learning to optimize based on MCC and attempts to
 114 optimize on a different metric instead, namely the cross
 115 entropy loss. The benefit is that model evaluation is done
 116 independently of model training, avoiding any data leakage
 117 and increasing the reliability of the model on unseen data.

118 4. Data Description & EDA

119 This project assumes the Meat Freshness Image Dataset
 120 ([Vinayakshanawad, 2020](#)) is the dataset provided by the
 121 client. The data consists of two folders for train and test
 122 datasets. The images are 416 x 416 pixels with the train
 123 dataset having 1,816 images and test dataset having 452
 124 images. All images are of red meats.

125 There are three classes of images as discussed in Assump-
 126 tions section: fresh, half-fresh and spoiled.

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Figure 1. Sample Image per Class

During EDA, the class balance and pixel value frequency was explored to see if there was any abnormalities with the dataset before pre-processing. For class balance, the three classes were relatively balanced within the training dataset as shown below.

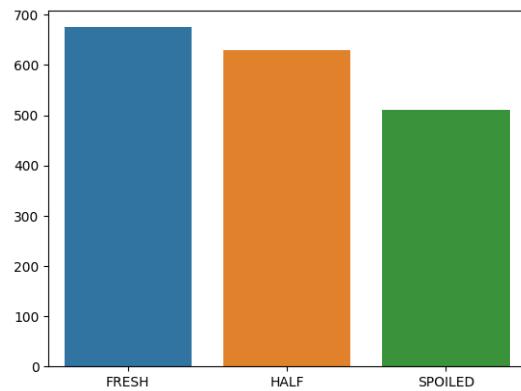


Figure 2. Number of Images per Class

For pixel value frequency, it can be determined that the three classes have distinct distribution of pixel value frequencies as shown below.

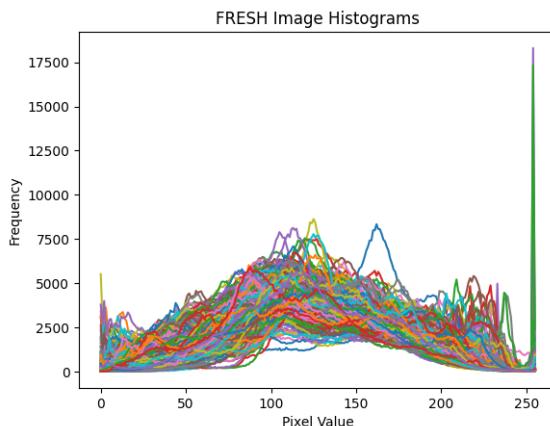


Figure 3. Pixel Value Distribution for Images of Fresh Meat. Pixel value from darker (0) to lighter (255).

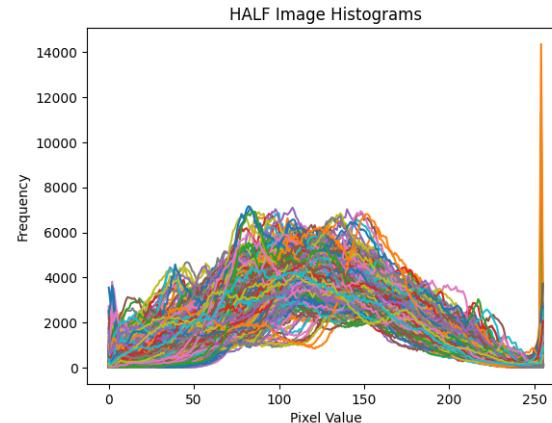


Figure 4. Pixel Value Distribution for Images of Half-Fresh Meat. Pixel value from darker (0) to lighter (255).

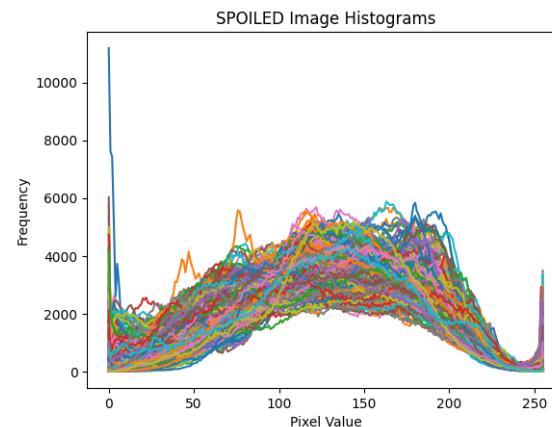


Figure 5. Pixel Value Distribution for Images of Spoiled Meat. Pixel value from darker (0) to lighter (255).

The distribution is significantly concentrated on the lighter pixels (255) for fresh meats while the distribution is concentrated on the dark pixels (0) for the spoiled meats. Half-fresh meat also has a distribution that is more concentrated on the lighter pixels than the spoiled meats. This is reasonable since on most meats the first sign of rot can be visibility detected by darker colored areas on the meat.

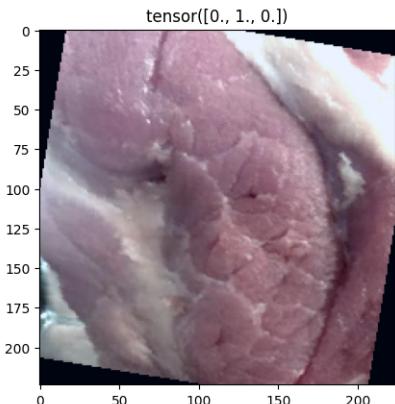
5. Preprocessing

For pre-processing, augmentation was applied to the dataset in order for the models to be trained on more data with noise and also not overfit. The training dataset was split into training and validation and a class and pipeline transformation function was established to augment the dataset, the transformation function did the following on the training dataset:

- 165 1. Random Resized Crop
- 166 2. Random Horizontal Flip
- 167 3. Color Jitter
- 168 4. Random Rotation
- 169 5. Normalize per standard (mean=[0.485, 0.456, 0.406],
- 170 std=[0.229, 0.224, 0.225])
- 171
- 172

173 For the validation dataset, only standard augmentation was
174 done:
175

- 176 1. Resize
- 177 2. Center Crop
- 178 3. Normalize per standard (mean=[0.485, 0.456, 0.406],
- 179 std=[0.229, 0.224, 0.225])
- 180
- 181
- 182



196 Figure 6. Sample Image after Transformation
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6. Algorithm and Modeling

6.1. ResNet

203 One of the models utilized to predict the freshness of the
204 meat based on its image is ResNet (He et al., 2016). ResNet
205 is a convolutional neural network architecture that intro-
206 duced residual blocks which allowed for effective training
207 of deep neural networks. To fit ResNet for this paper's
208 freshness prediction task, the final layer is reshaped to have
209 the same output count as our image classes.

210 Two variants of the ResNet architecture were used to train
211 models which are ResNet-18 and ResNet-50. The former is
212 18 layers deep while the latter is 50 layers deep. For model
213 training, two transfer learning strategies were utilized. The
214 first is feature extraction which utilized pre-trained weights
215 of ResNet to get the image embeddings, and only the para-
216 meters of the final layer were updated during training.
217 The pre-trained weights used for feature extraction were
218 acquired from the PyTorch library (Paszke et al., 2019). The
219

second strategy is to fine-tune the whole ResNet architec-
ture by updating all model parameters using the dataset.
After training, the models were evaluated on the test set and
the models' performance metrics and final hyperpara-
meters used are reported in Tables 4 and 5 below. All model
weights are saved after training should the client decide that
the solution proposed is suitable for deployment.

Table 4. ResNet Model Performance
FE: Feature Extraction, FT: Fine-tuning

MODEL	ACCURACY	PRECISION	RECALL
RESNET 18-FE	82.71%	84.66%	83.71%
RESNET 18-FT	93.13%	93.97%	92.85%
RESNET 50-FE	88.03%	88.35%	88.86%
RESNET 50-FT	84.70%	84.50%	86.14%

Table 5. ResNet Hyperparameters

HYPERPARAMETER	VALUE
BATCH SIZE	32
EPOCHS	5
OPTIMIZER	ADAM
LEARNING RATE	0.001
LOSS CRITERION	CROSS-ENTROPY

The best performing model based on test set accuracy, pre-
cision, recall is the fine-tuned ResNet-18. Interestingly, the
results show that a deeper network doesn't necessarily trans-
late to better model performance. While the ResNet-50 fea-
ture extraction model performed better than the ResNet-18
feature extraction model, the ResNet-18 fine-tuned model is
superior to the ResNet-50 fine-tuned model. The ResNet-18
feature extraction model also performed better than both of
the ResNet-50 models. This is probably due to the relatively
small number of samples used to train the models. The
deeper ResNet-50 architecture might be over-fitting or is not
learning better representations of each image class but this
is still speculated given the high complexity of ResNet-50.

6.2. UNet with Dense Net

A semi-supervised approach can also be used to classify
images, one of the more common methods is image seg-
mentation. Image Segmentation is a method of image rep-
resentation that uses a set of "masks" which act as a form of
ground truth to segment specific portions of our images and
these would be the representational patterns that we would
like to capture. In this case, the pattern of interest is the
rot present in an image, while identifying rot is a subjective
matter it is entirely possible to map this as an input feature
to a model and have its representations capture. This model
would be able to capture image segments on related images.
To achieve this, the model typically uses a combination of

Double Convolutional Neural Networks with a structure called skip-connections which skip some of the connections in a neural network and feeds the output of one layer as input to the other layers. Skip-connections greatly reduce the complexity of loss surfaces, making it easier for optimizers to reduce loss while ensuring that feature representations are reused (Li et al., 2017). The images for a sample image and prediction are shown below (areas in yellow are rotten areas of the meat as identified by the model).

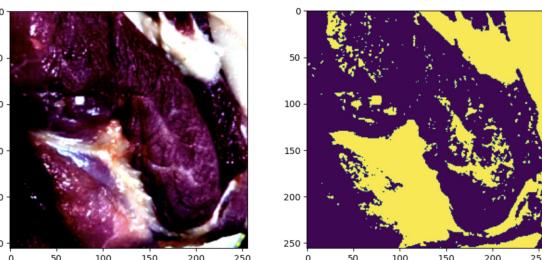


Figure 7. Sample Image and Prediction

The algorithm used to achieve this was UNet (Ronneberger et al., 2015), it uses Double Convolutional layers to identify and extract features from the input image and uses skip connects to reuse these features in a related layer. The idea is that each feature set captured in a layer is captured in a layer connected by a skip connection and passed to the next layer to compute the representation segment. Since this task outputs a set of image patterns the ideal outcome would be identifying the quality of the outputs in terms of the intersection and the overlap resulting from the predictions and the image masks. The loss functions capable of representing this effort are Dice loss and Jaccard loss which broadly look at the ratio of the intersection to the union, so concretely both would have a measure of how well the model can segment the patterns of interest from a given input image.

The extracted image segmented predictions were passed as input features to a DenseNet model and predictions were output based on the segments captured.

Table 6. UNet and DenseNet Hyperparameters

HYPERPARAMETER	VALUE
BATCH SIZE	8
EPOCHS	5
OPTIMIZER	ADAMW
LEARNING RATE	0.001
LOSS CRITERIA	JACCARD LOSS & CROSS-ENTROPY

The segment of interest in this case is the rot present in the image and this was one-hot encoded when it was passed to

the DenseNet model. The outputs from this model would be used to classify the image.

Table 7. UNet with Dense Net Model Performance

ACCURACY	Precision	Recall
35.25%	100%	35.25%

This model, however, seems to show very poor performance in classification because the segments may not be fully interpreted by the model. While a larger model like ResNet learns several feature representations from an image with increasing complexity, this model learns only from the image segments captured and can only use this limited information for inference. As observed in the model performance, the recall is quite low which means that the model is incorrectly classifying meat but the precision is quite high which implies that the model is very accurate in identifying the correct classes. The resulting misclassification cost is also quite high in this case because every incorrect prediction would result in a very large cost to the business and as a result, this model was not used as the final model.

7. Model Evaluation

To evaluate the model performance, the primary metrics used were accuracy and Misclassification Cost (MCC). While accuracy is commonly understood as the model's predictive capability, another method of assessment would be MCC which uses the underlying principles of the Expected Value Framework (EVF) to identify the cost to a company based on the predictions from this model. MCC can be interpreted as the amount of money lost by the business should the model misclassifies an image. This would determine how the model can affect the business.

The MCC is calculated based on an individual value resulting from the actual value vs the predictions as referenced in Table 2 and 3 and cumulatively they would form a cost representing the amount of money lost by the business per misclassified image. This would prioritize the model development to ensure that specific costly misclassification, which is predicting actual spoiled as fresh or half-fresh, is avoided while ensuring that the model has a high accuracy. The cumulative MCCs shown in Table 8 indicate the potential costs of using the model in one business day. It means that if daily benefits the client would obtain with this technology, such as labour cost reduction, outweigh the cumulative MCC, the client could consider the introduction of the technology.

275
276 **Table 8.** Evaluation on MCC
277 FE: Feature Extraction, FT: Fine-tuning

MODEL	ACCURACY	MCC
RESNET 18-FE	82.70%	\$886
RESNET 18-FT	93.13%	\$5,076
RESNET 50-FE	88.03%	\$242
RESNET 50-FT	84.70%	\$316
UNET	35.25%	\$89,411



Figure 8. Confusion Matrix of 18FT



Figure 9. Confusion Matrix of 50FE

318 The ResNet 18-FT model has exceptionally higher precision
319 and recall scores on test data compared to other models and
320 this also shows that it is able to largely generalize on the
321 dataset and given that the dataset is small it can identify
322 the patterns correctly without compromising too much on
323 the quality of the predictions. However, the ResNet 50-
324 FE yielded the lowest MCC despite having lower accuracy,
325 precision and recall compared to ResNet 18-FT. This means
326 that ResNet 50-FE is the best model for this paper's business
327 case.

328 The reason why the MCC evaluation chose a lesser perform-

True label	SPOILED	0	499.75	99.9
	HALF-FRESH	4.5	0	3.5
	FRESH	9	4	0
	SPOILED	HALF-FRESH	FRESH	Predicted label

Figure 10. Matrix of MisClassification Cost(MCC)

ing model as the most appropriate one for the business case lies in how the MCC matrix penalizes the mistakes of the models. Looking at the confusion matrix of ResNet 18-FT in Figure 8, it misclassified 10 spoiled meat images as half-fresh, resulting in an MCC cost of \$4,998 on these mistakes alone. Contrast this with the ResNet 50-FE model in Figure 9, where it didn't misclassify any spoiled meat images but made most of its mistakes misclassifying half-fresh meat images. The ResNet 50-FE model did not incur any heavy cost in misclassifying spoiled meat, and all of its other mistakes only incurred a cost of only \$242. This result is in line with the business case where selling a customer spoiled meat will incur a very a high cost, and consequently a model that misclassifies spoiled meat will incur a significant cost to the client.

In summary, it is recommended that the model to be deployed in production is the ResNet 50-FE model, since it will yield the client the lowest possible cost when this model makes mistakes.

8. Interpretation

SHAP (Lundberg and Lee, 2017) and LIME (Ribeiro et al., 2016) paradigms were used to understand how the model works and improve interpretability of the model, to identify what features or areas of the image the model uses to identify the class of a particular piece of meat. Results from SHAP were inconclusive and ambiguous, however, results of using LIME offered valuable insight into what the model sees and uses to perform classification. Some results from the LIME classification are given below.

The images in the middle represent the super pixels or segments used as important features used by the model to classify the image for a specific class and the images on the right represent the probabilistic regions used by the model for classification; with regions in green indicating a higher probability that the model used those regions while regions

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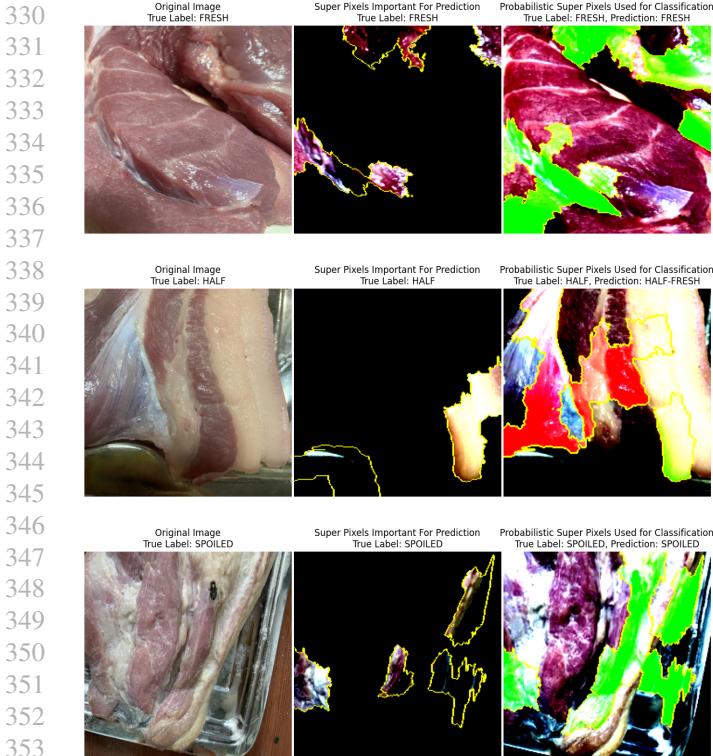


Figure 11. Example of Lime Interpretations for each of three classes: Fresh (Top), Half-Fresh (Middle) and Spoiled (Bottom)

363 in red indicating a lower probability for the same.

364 It is observed that the model is able to identify the key
365 regions of rot in the spoilt meat and use those regions for
366 determining it's classification. On the other hand, the model
367 is also able to identify similar segments of freshness in fresh
368 meet and classify those correctly as well. This suggests
369 that the model developed is able to differentiate between
370 spurious features in the image and pick out the important
371 segments of the image that will help it in classification.

372 A similar analysis of a few misclassified images (12) sug-
373 gests the same. Though the model is unable to correctly
374 classify these food items, it is still successful in identifying
375 appropriate areas of the image which can serve as important
376 input features in the final decision.

377 It can hence be concluded that while the model does not
378 yield 100% accuracy, it's current decision making is based
379 on identifying valid areas of the image that represent fresh
380 or spoiled meat, rather than using spurious areas such as
381 portion of packaging or image background to determine the
382 same.

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385 sustainability is being highlighted. If food waste can be
 386 reduced by this technology, it can be a marketing advantage
 387 and can contribute to an increase in corporate value.

388 However, there are also barriers to overcome in order to
 389 create the above-mentioned value. If the applicable ingre-
 390 dients are limited (such as only meat), supermarkets will
 391 not be interested in this technology. To introduce it into
 392 actual operation, it would be necessary to be applicable to
 393 all kinds of perishable foods. Also, freshness standards may
 394 differ depending on the weather at that time. To address
 395 these issues, a huge amount of training data and time, as
 396 well as new features to consider additional factors such as
 397 humidity levels, are needed. In addition, this model assumes
 398 that clear images are available for each slice of meat. In
 399 other words, it assumes that each product on display can be
 400 photographed one by one with adequate lighting and that
 401 the meat is not blocked by any packaging or other material.
 402 If a model is improved with cameras and object identifica-
 403 tion/image processing such that it can analyze the freshness
 404 of multiple products at the same time from a single image
 405 containing multiple products with packaging, the usability
 406 of this model will be further enhanced.

407 Additionally, the interpretation portrayed using LIME can
 408 be used in multiple ways. At any given point, it can be used
 409 to generate a similar probability map and check what are the
 410 areas of rot on the meat that the model is using to make it's
 411 prediction. This can help understand if the model is 'seeing'
 412 the correct features. This utility can be further extended to
 413 monitor model performance, and track deterioration if the
 414 model starts using irrelevant or relatively unimportant areas
 415 of the image to make its classification. Any deterioration
 416 or change in the probability maps would signal a need to
 417 retrain the model or deploy new models

418 In this project, a supermarket is assumed as a client. How-
 419 ever, this technology can also have other applications. For
 420 consumers, if a device that can detect the food conditions
 421 can be installed in their refrigerators, they can reduce food
 422 expenses and waste at home.

423 Finally, the utility and value of this model can be further
 424 enhanced by merging it with data-driven decisions such as
 425 maintaining inventory based on demand forecasting and
 426 other business analytics techniques to add multiple layers
 427 of safety in terms of food freshness and wastage.

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463 Reproducibility

464 The source code and data used to generate the
 465 results presented in this paper are available at:
<https://github.com/TheLohia/Phteven>.
 466 This contains: (i) Model training and evaluations scripts
 467 (ii) Jupyter notebooks for model experiments and (iii) web
 468 demo for the model