Artificial Vision System for Meat Quality Gradation

B. Tech Major Project Report
By :

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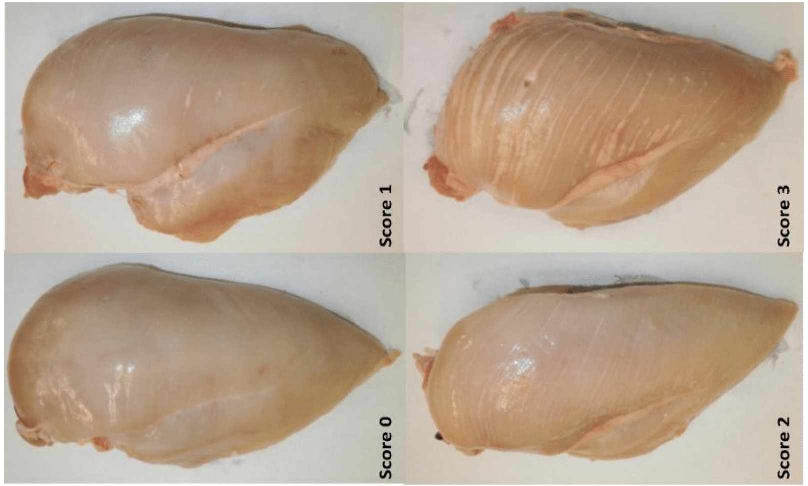
Kingshuk Chatterjee

Problem statement

- A rapid system for meat quality assessment is needed to guarantee the quality of meat.
- We plan to solve this problem by developing a mobile application to help users determine meat freshness in real-time.



Importance of work

- In today's world, food spoilage is a crucial problem as consuming spoiled food is harmful for consumers.
- Meat is a kind of perishable food that easily decays.
- As the number of meat consumers increases in the meat industry, the demand for meat supplies also rises. Determining meat freshness, therefore, is the primary consideration of the meat customers.
- Due to covid, many people are ordering food items online. This has increased the necessity for real-time meat quality assessment through images.
- It will be helpful for customers who don't know how to check meat quality by seeing or touching it.

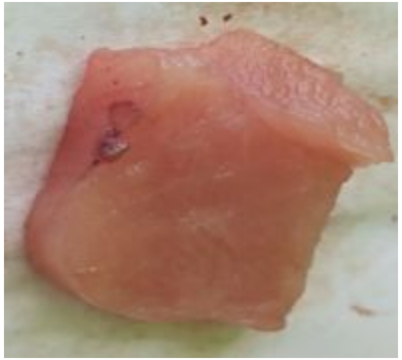
Dataset Preparation

1. Chicken

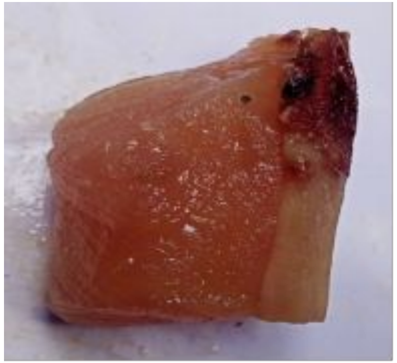
a. Breast meat portion was used as a sample for the dataset. The chicken breast was cut to various lengths and widths but with almost uniform thickness

b. The chicken meat images were captured starting from day 1 and at every 2 days' interval till 13th day. Chicken was stored in a freezer in the intermediate days with a temperature of 0 degree Celsius.

c. Meat images classified as consumable were taken till 5-6 days from day one of death, and meat classified as non-consumable were taken from 5-6 days of death till the 13th day.



Consumable



Non-Consumable

Dataset Size -
1) Consumable - 188
2) Non Consumable - 122

Dataset Preparation

2. Fish

a. The live Fish (Pabda) were sampled live from market.

b. The fish images were captured starting from day one of death and at every two days' interval till the 10th day. Fish was stored in a freezer in the intermediate days with a temperature of 0 degree Celsius.

c. Fish images classified as consumable were taken till 4-5 days from day one of death, and fish classified as non-consumable were taken from 5-6 days of death till the 10th day.

Consumable

Non-Consumable

Dataset Size -
1) Consumable - 60
2) Non Consumable - 80

Dataset Preparation

3. Prawn

a. Fresh white-leg prawn were sampled live from market.
b. The prawn images were captured starting from day one of purchase and at every one day interval till 7th day. It was stored in a freezer in the intermediate days with a temperature of 0 degree Celsius.
c. Images classified as consumable were taken till 3-4 days from the day one of death, and images classified as non-consumable were taken from 3-4 days of death till the 7th day.

Consumable

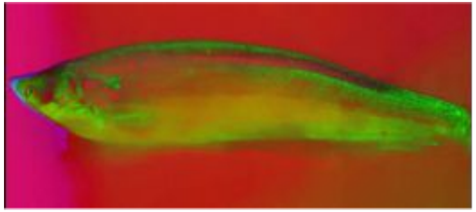
Non-Consumable

Dataset Size -
1) Consumable - 52
2) Non Consumable - 70

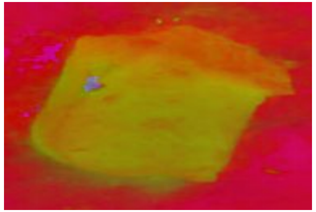
Methodology

1. Color Spaces

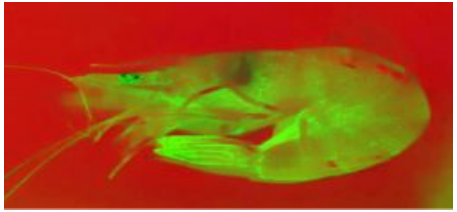
- The image captured is in RGB color space then converted to HSV color space.
- The use of HSV rather than RGB space is beneficial in texture analysis. Paschos [7] demonstrates that perceptually uniform spaces, such as HSV, outperform non-uniform RGB.



Consumable (HSV)



Consumable (HSV)



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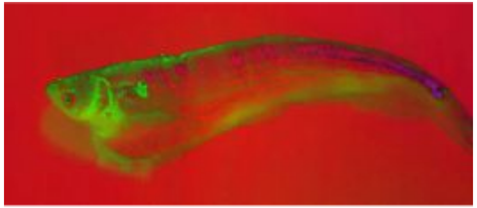
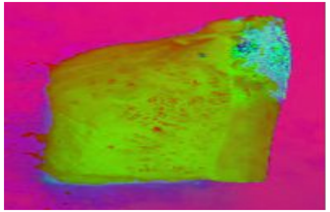
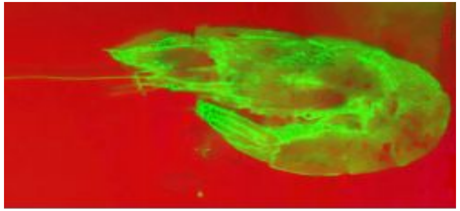


Non - Consumable (HSV)



Non - Consumable (HSV)

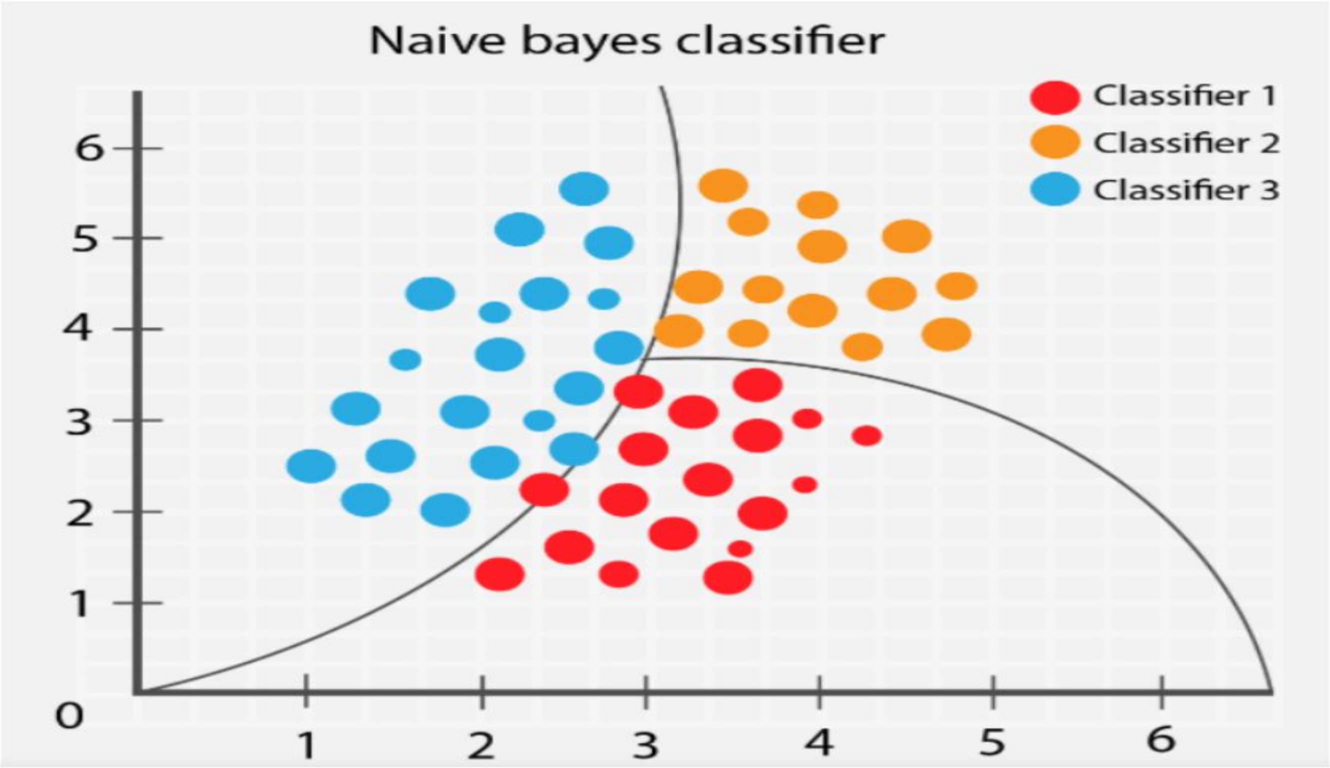


Non - Consumable (HSV)

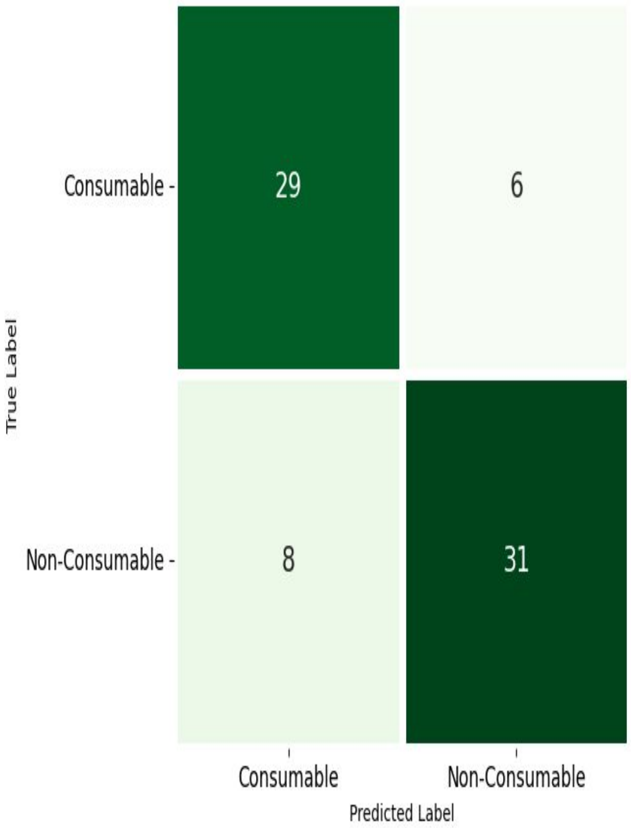
Methodology

2. Machine Learning Methods

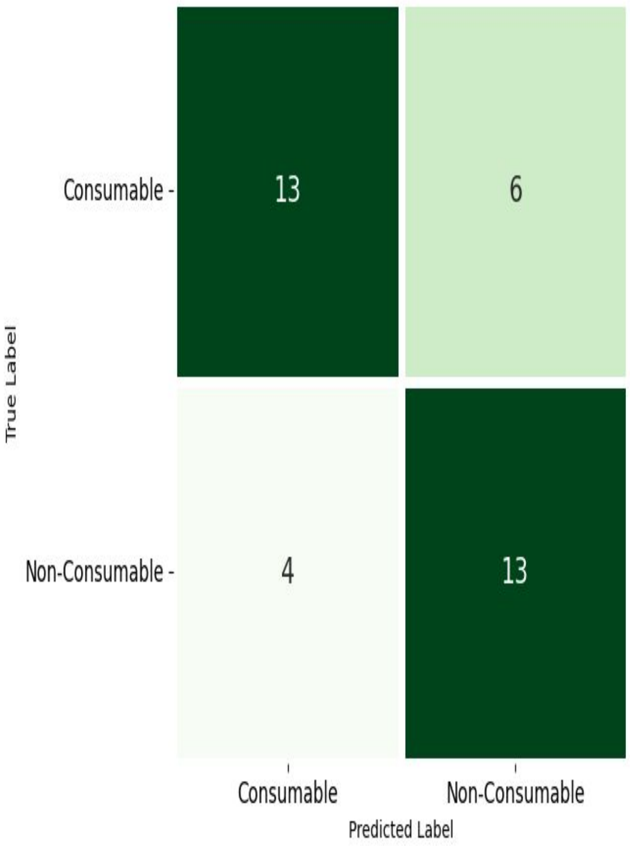
a) Naive Bayes



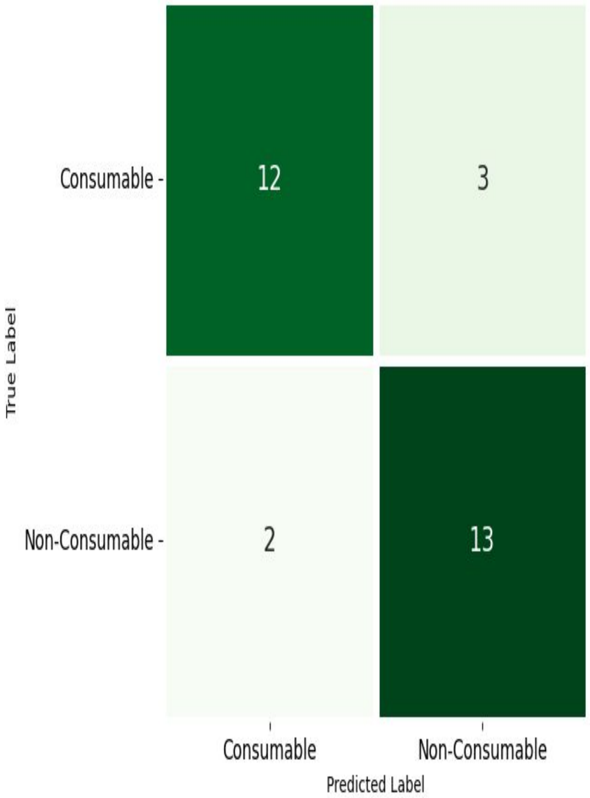
Methodology



Chicken Dataset (HSV)



Fish Dataset (HSV)

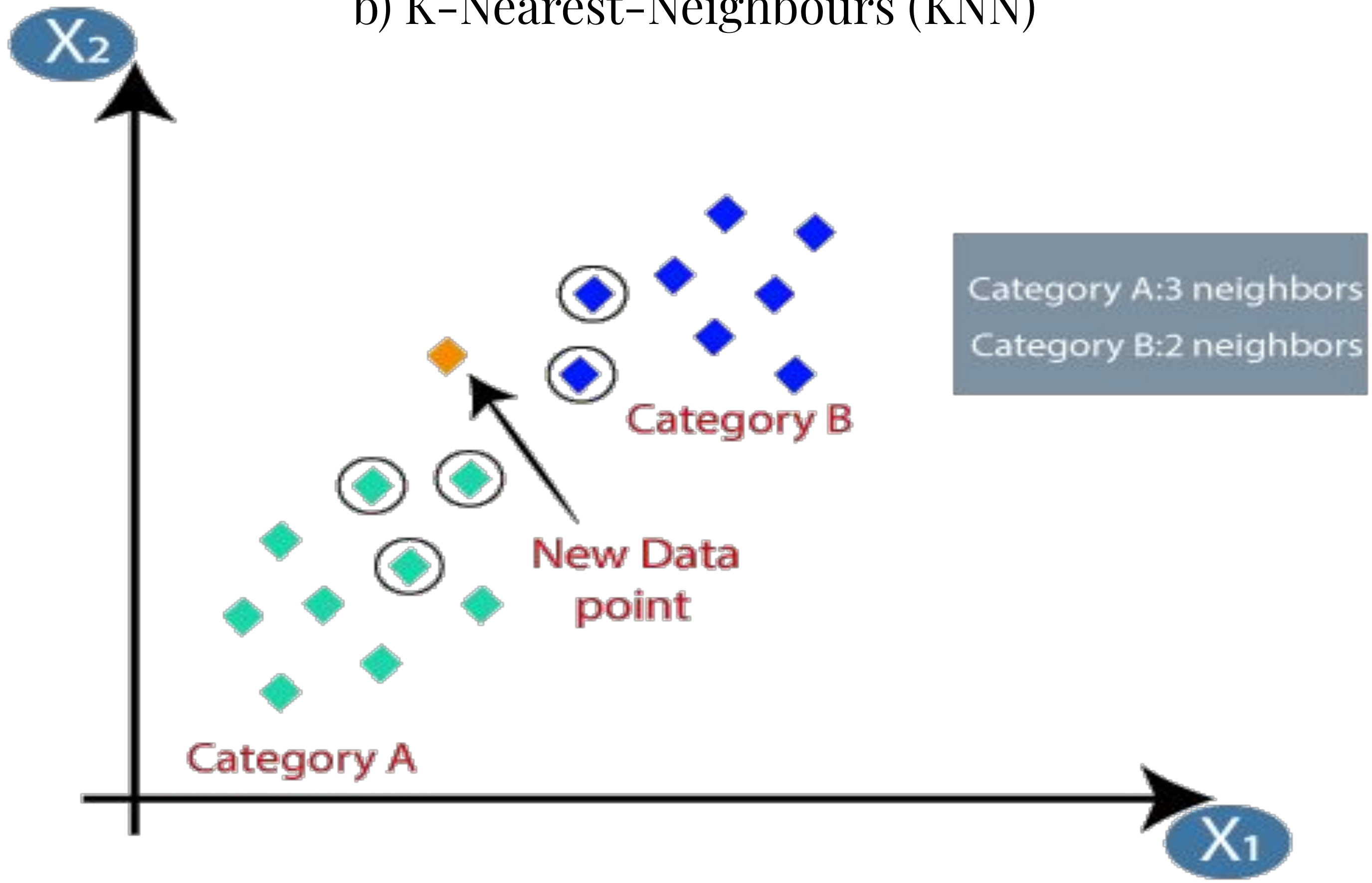


Prawn Dataset (HSV)

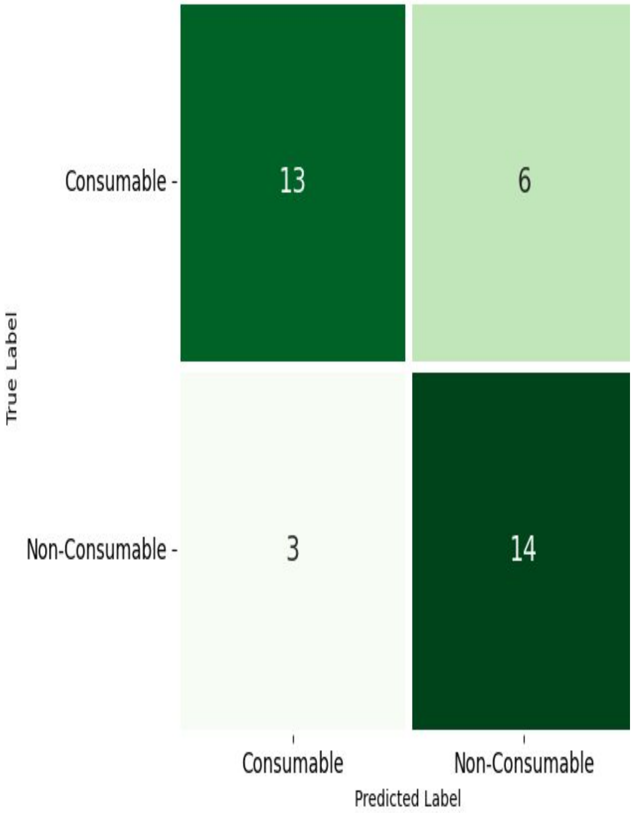
Methodology

2. Machine Learning Methods

b) K-Nearest-Neighbours (KNN)



Methodology



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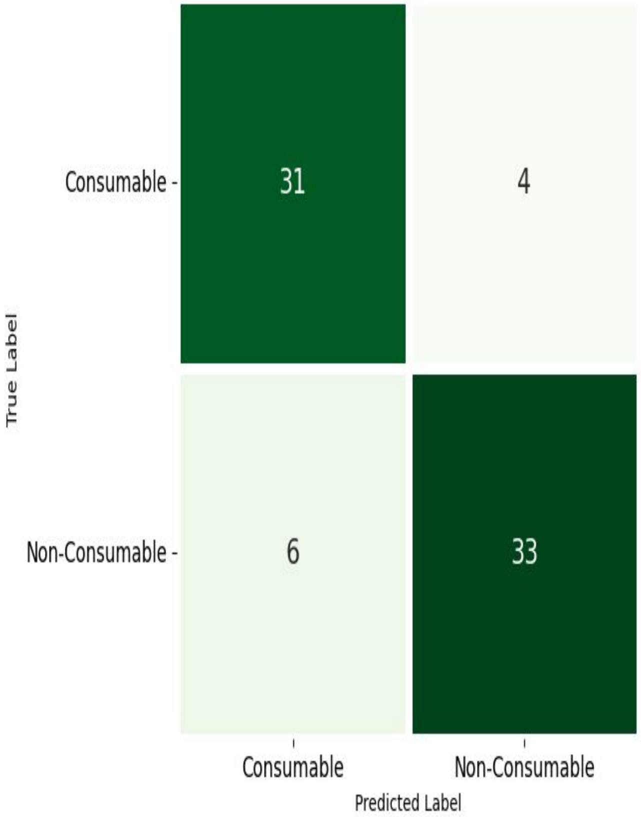
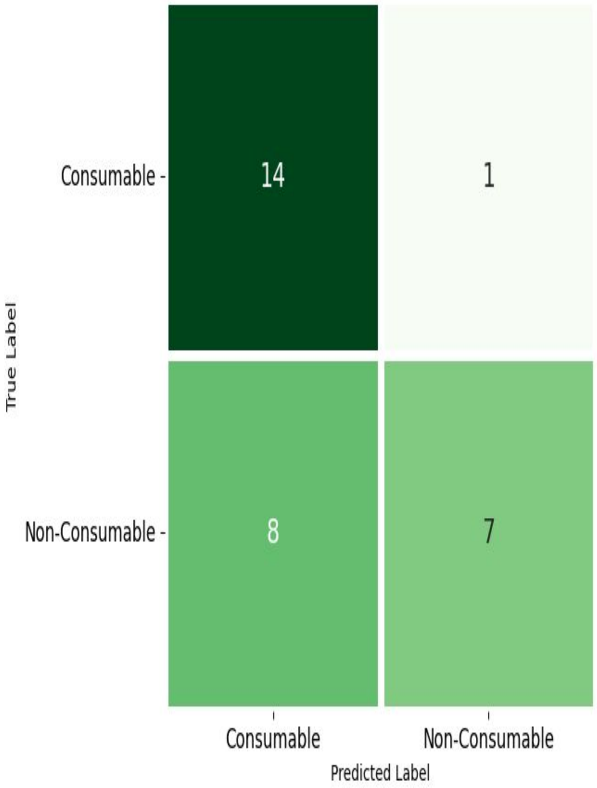


Fish Dataset (HSV)

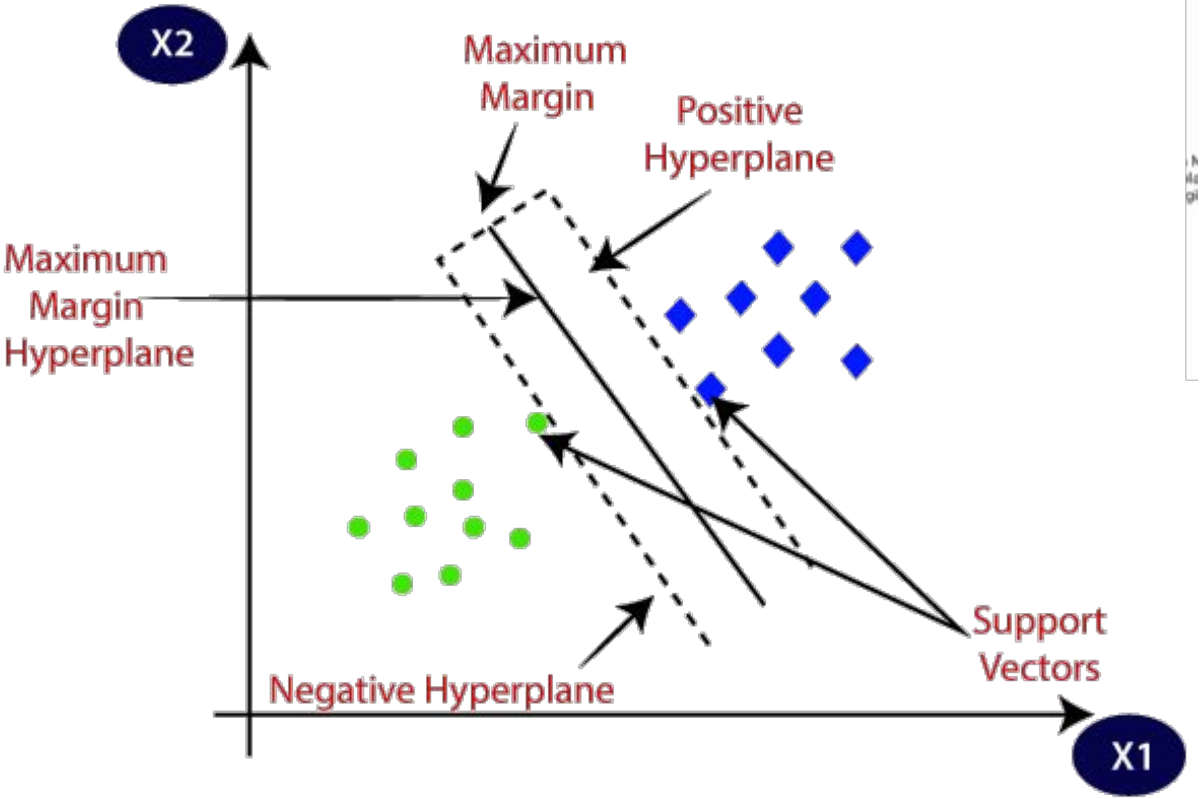


Prawn Dataset (HSV)

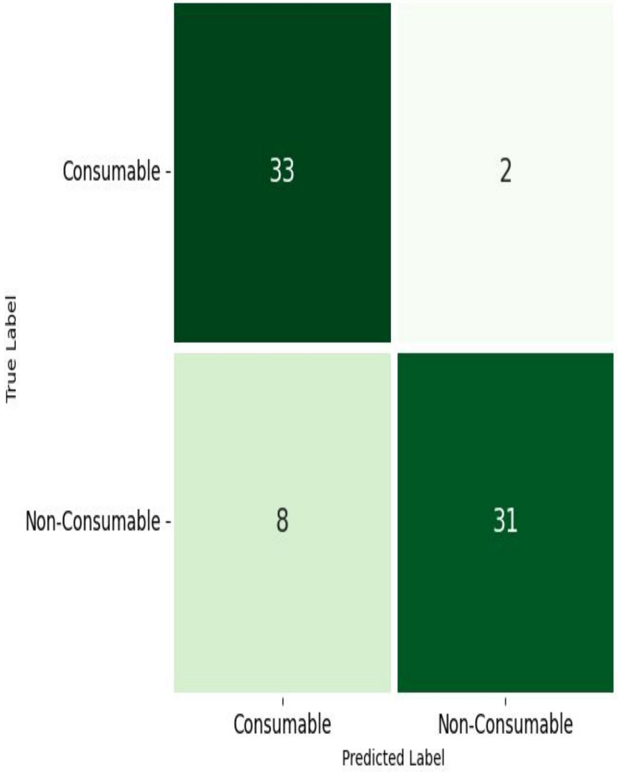
Methodology

2. Machine Learning Methods

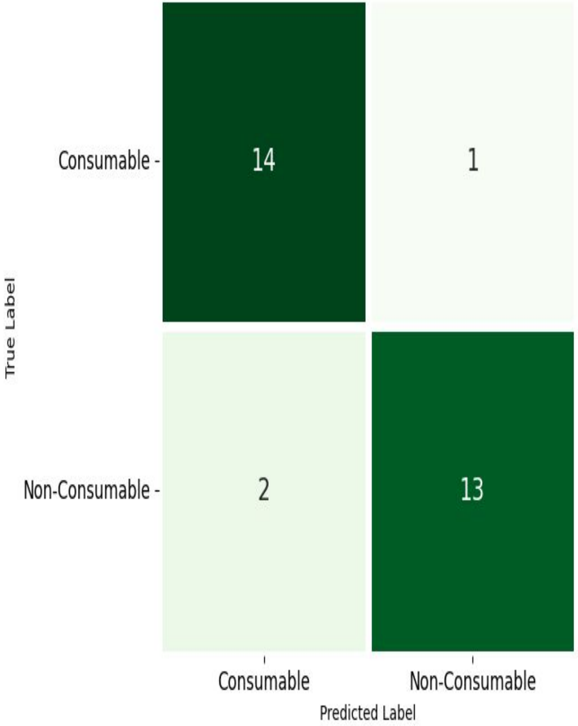
c) Support Vector Machine (SVM)



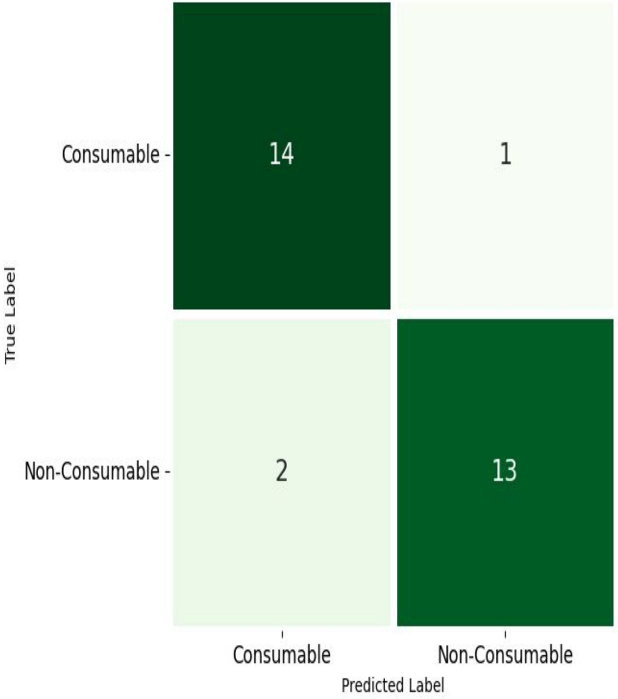
Methodology



Chicken Dataset (HSV)



Fish Dataset (HSV)

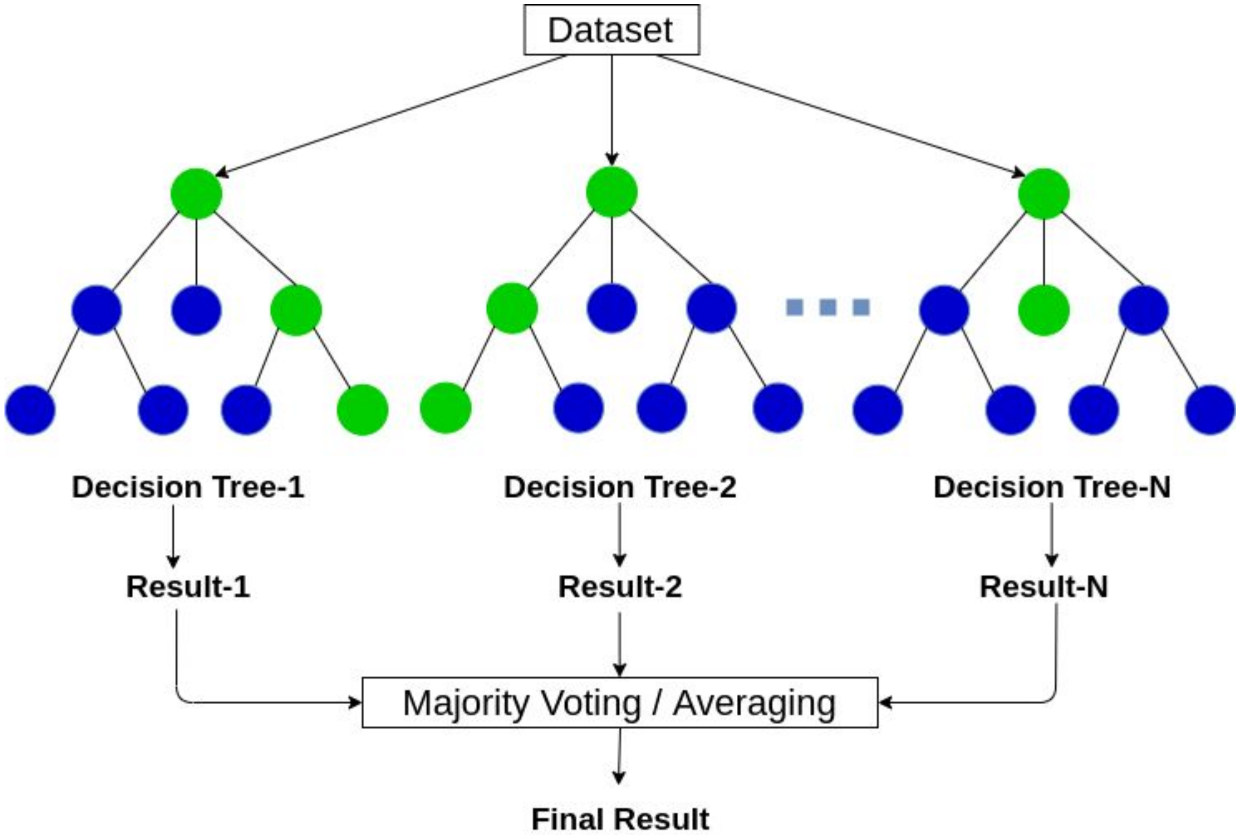


Prawn Dataset (HSV)

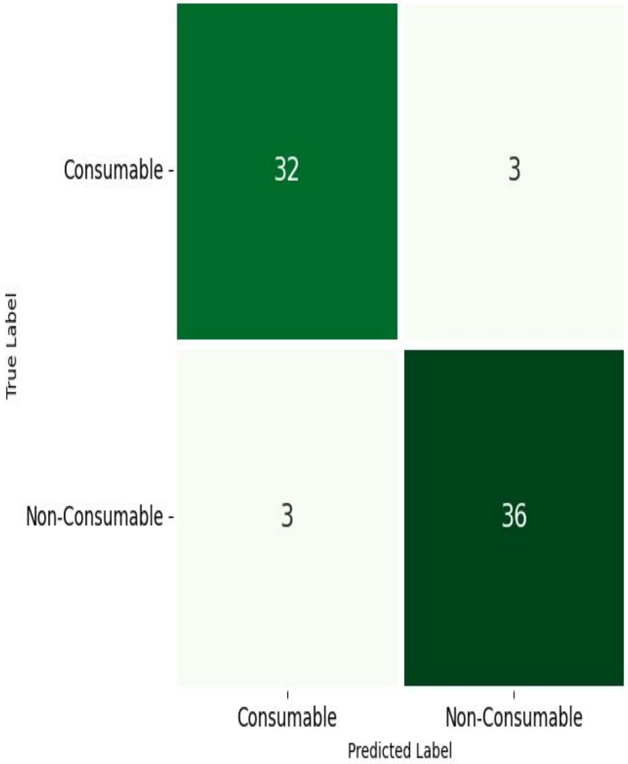
Methodology

2. Machine Learning Methods

d) Random forest



Methodology



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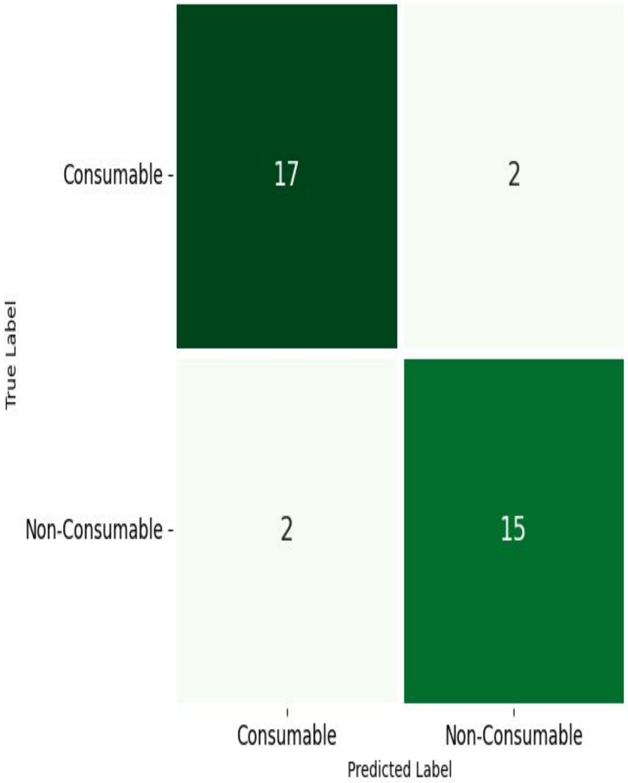
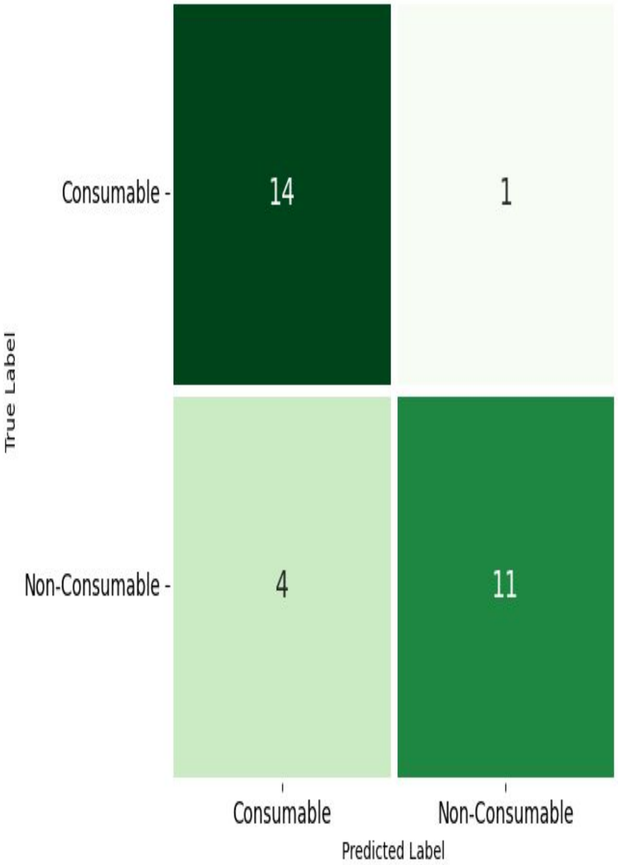


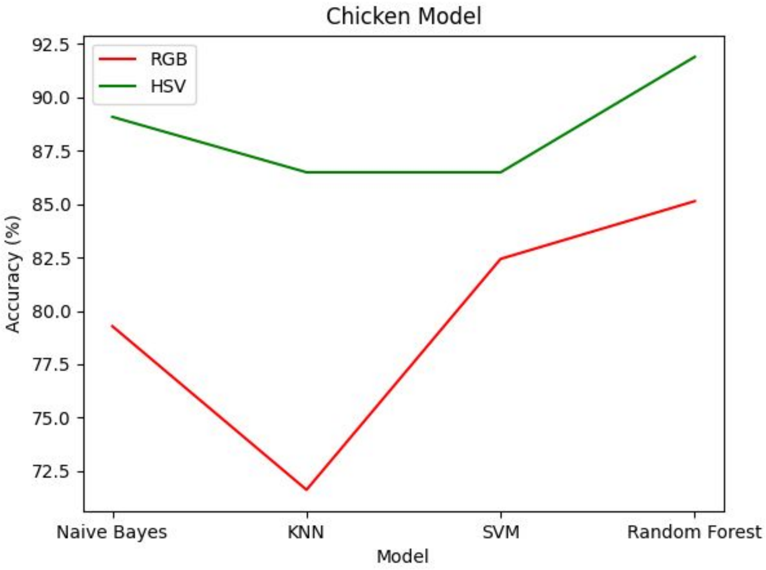
Fish Dataset (HSV)

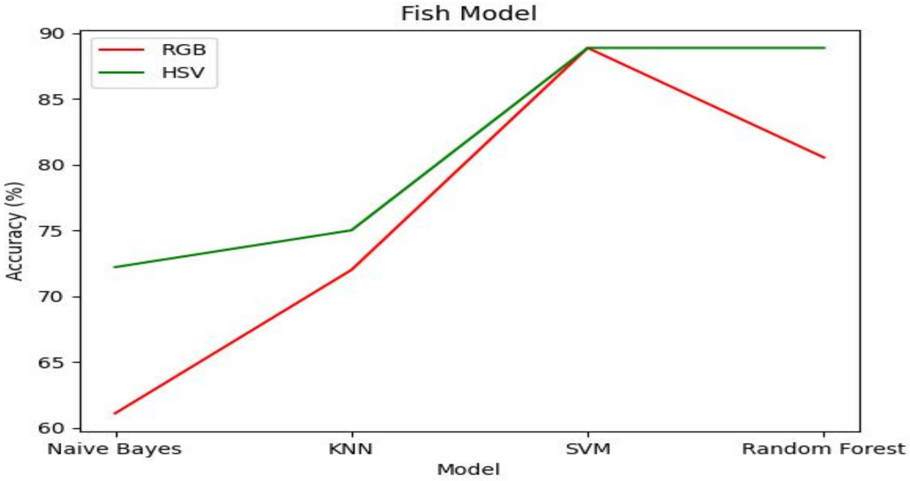


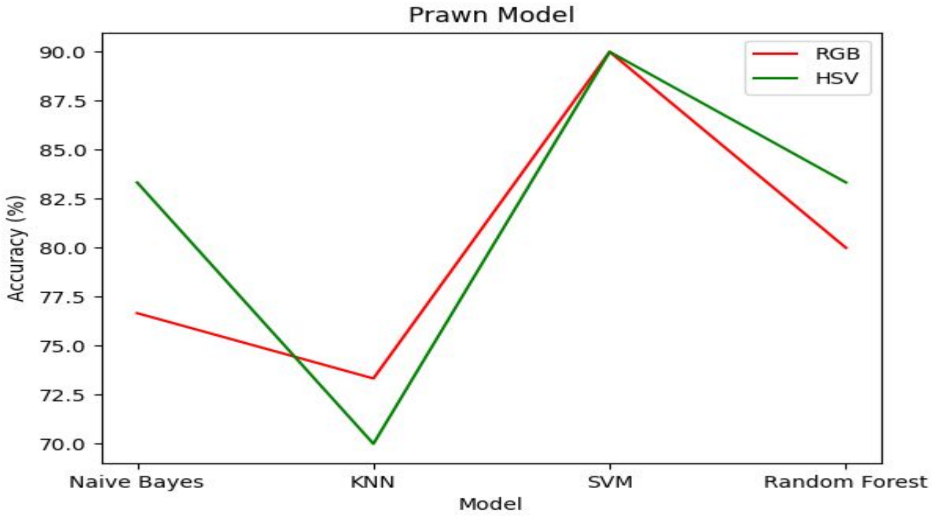
Prawn Dataset (HSV)

Summary

Machine Learning Model's Summary



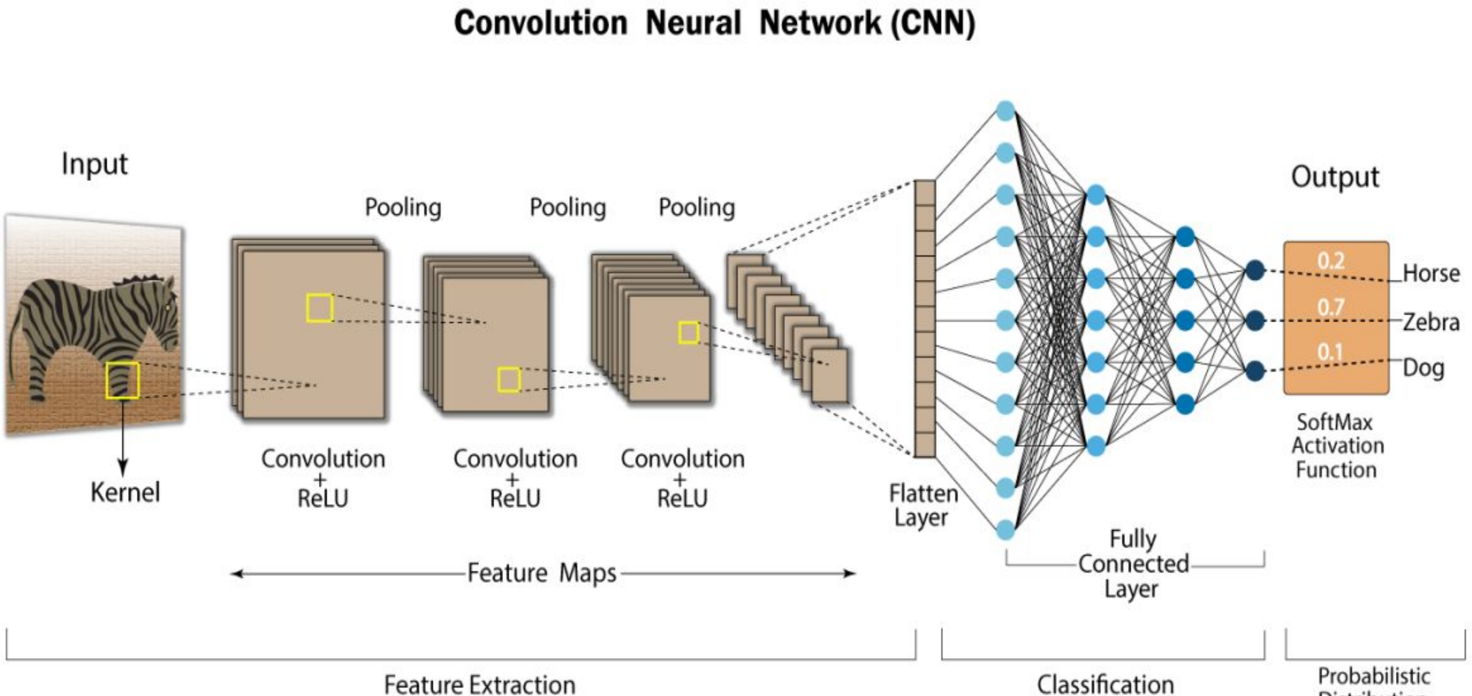




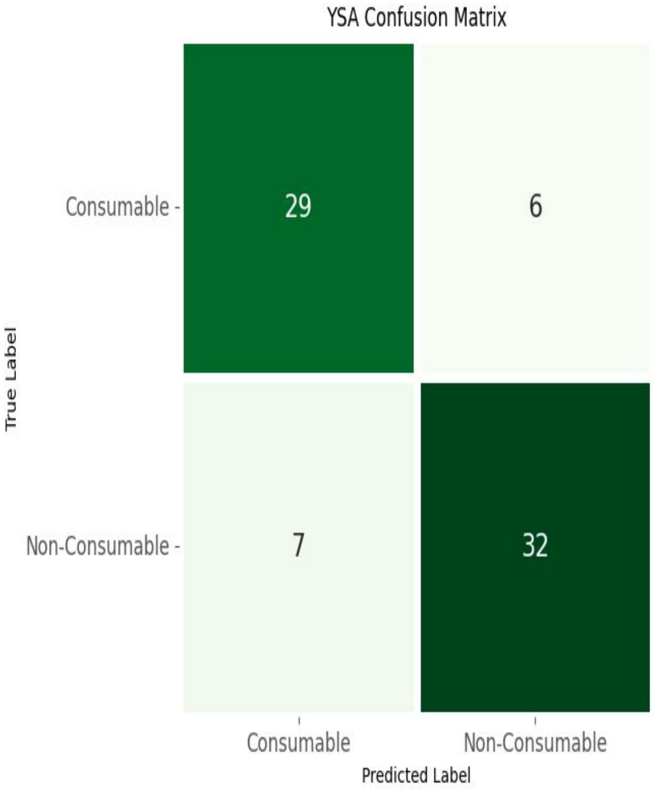
Methodology

3. Deep Learning Methods

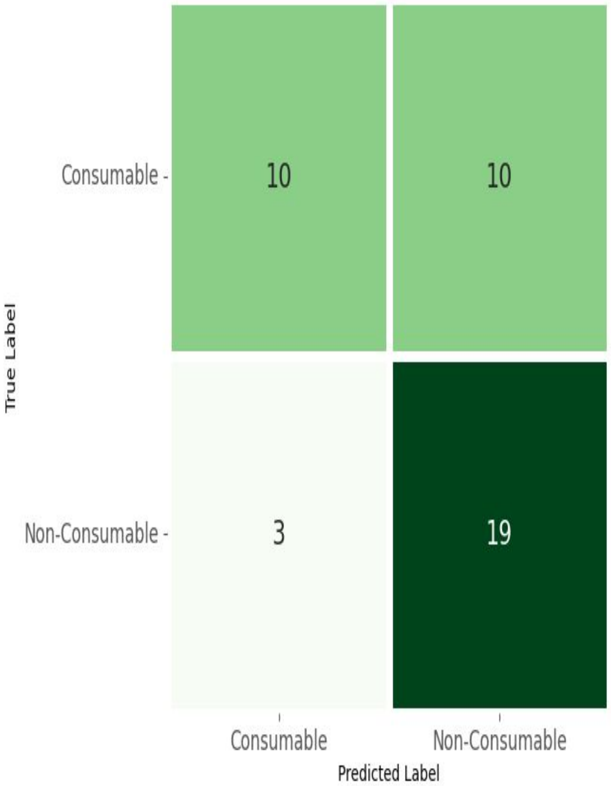
a) Convolutional Neural Network



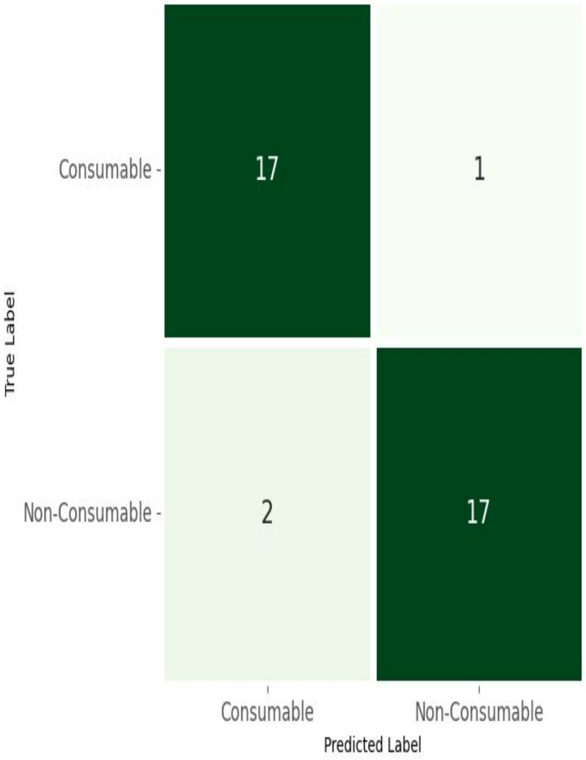
Methodology



Chicken Dataset (HSV)



Fish Dataset (HSV)

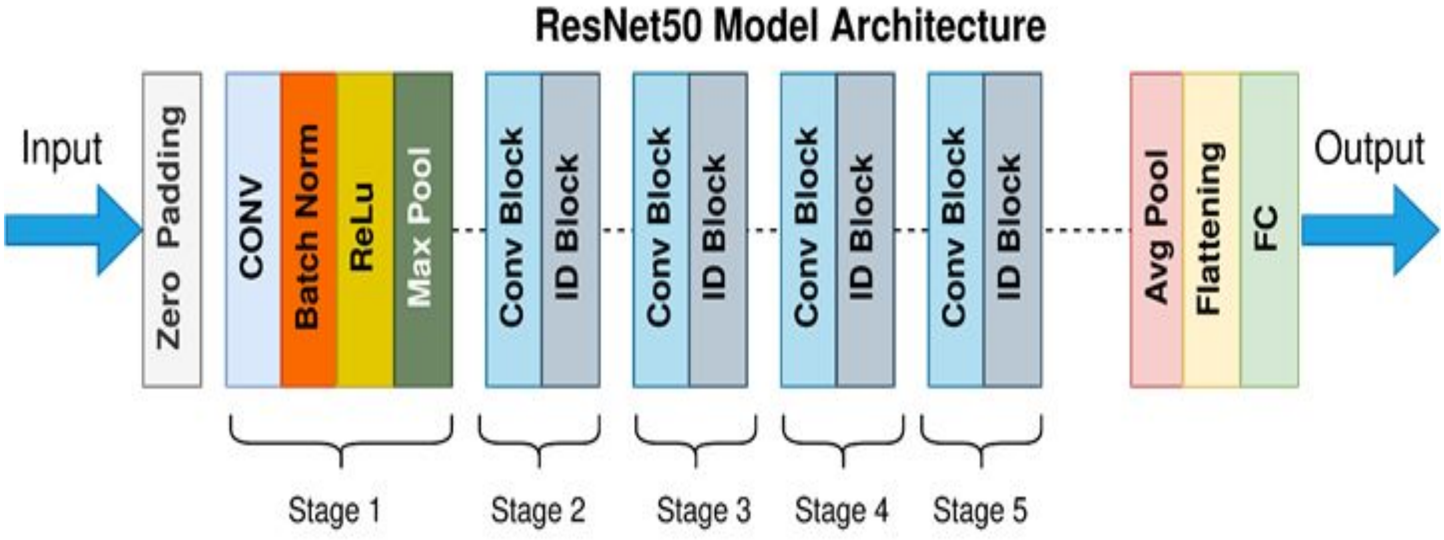


Prawn Dataset (HSV)

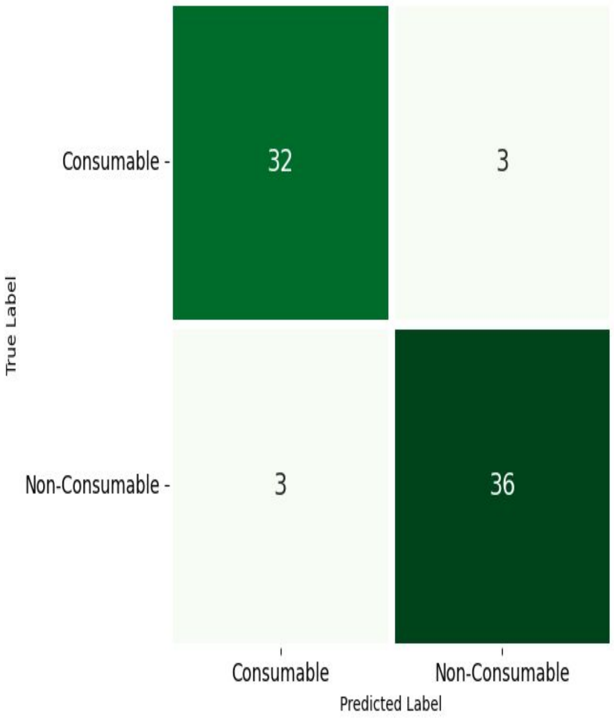
Methodology

3. Deep Learning Methods

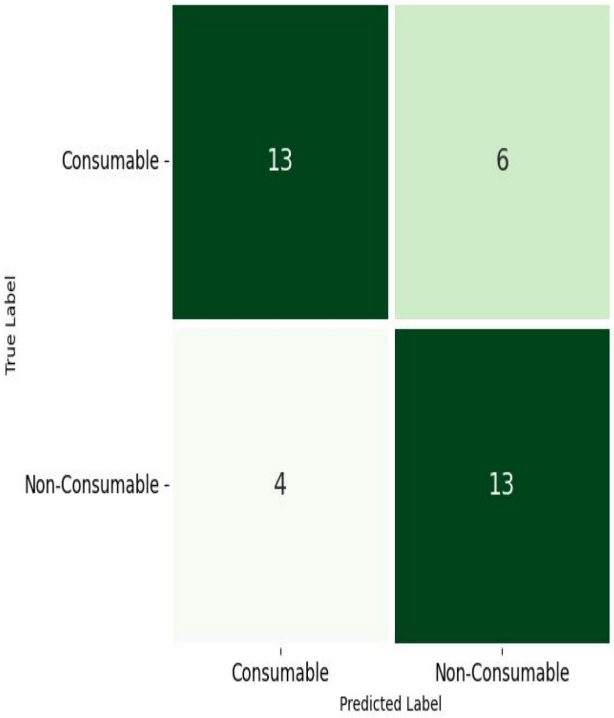
b) Residual neural network (ResNet)



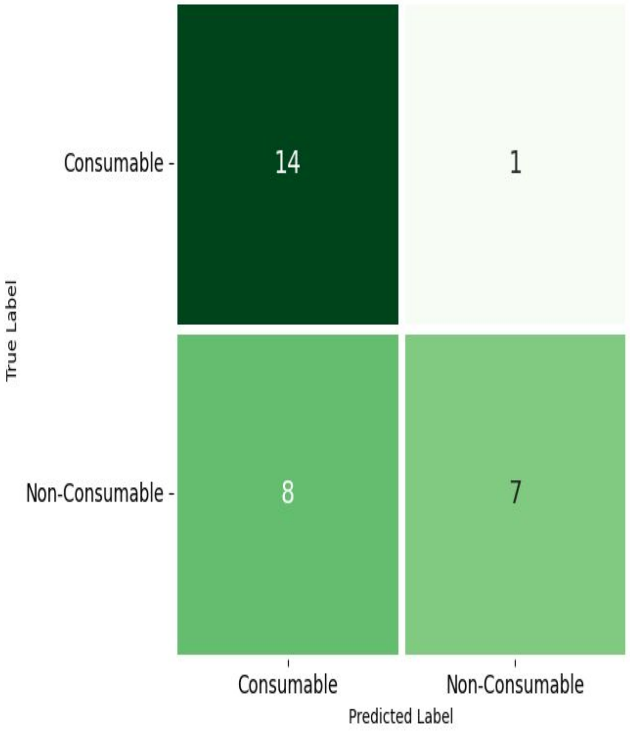
Methodology



Chicken Dataset (HSV)



Fish Dataset (HSV)

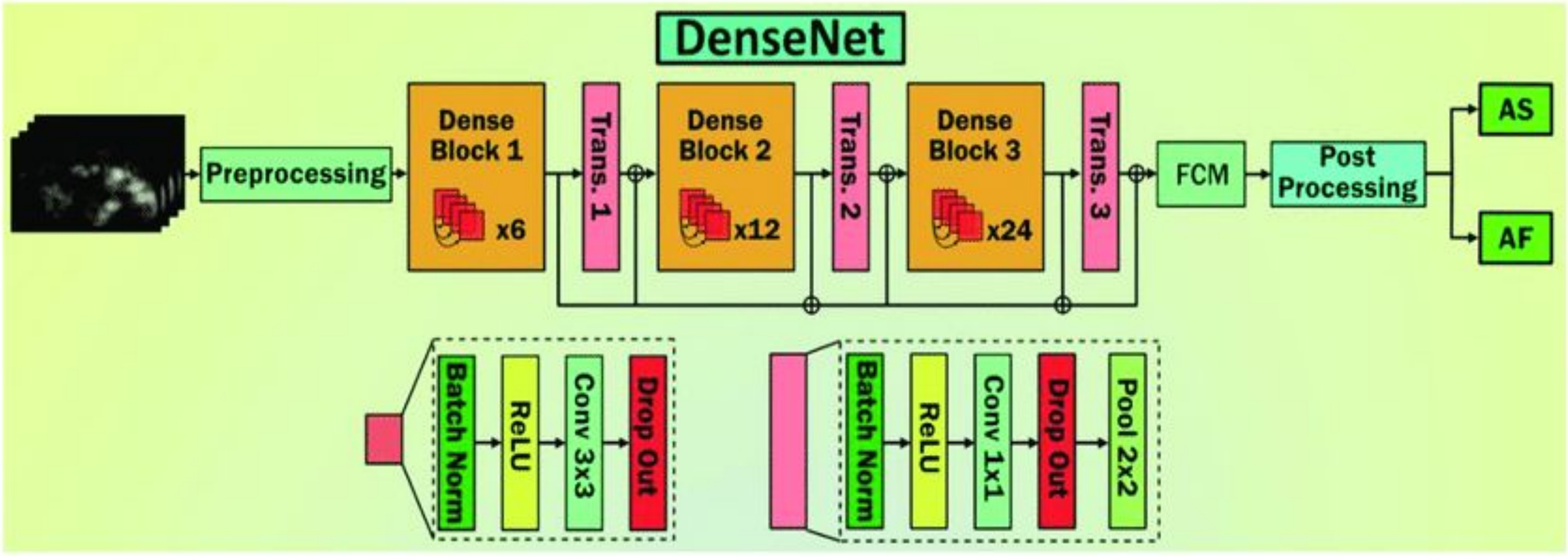


Prawn Dataset (HSV)

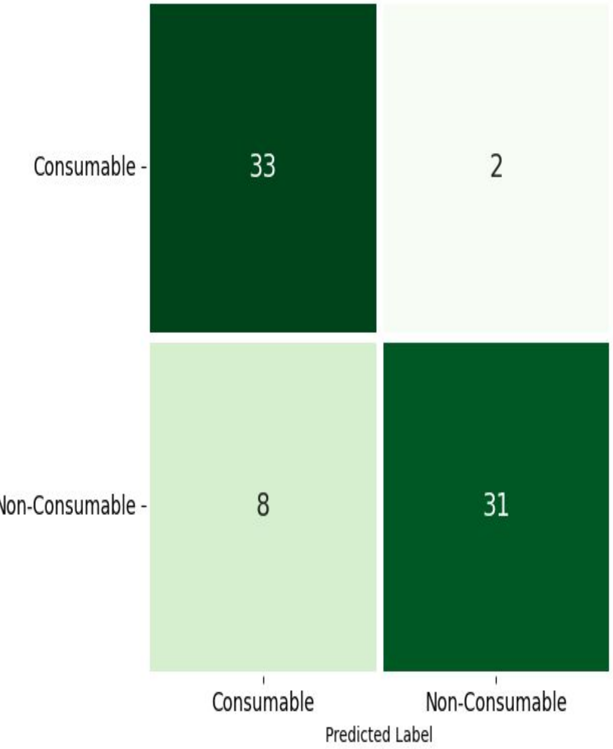
Methodology

3. Deep Learning Methods

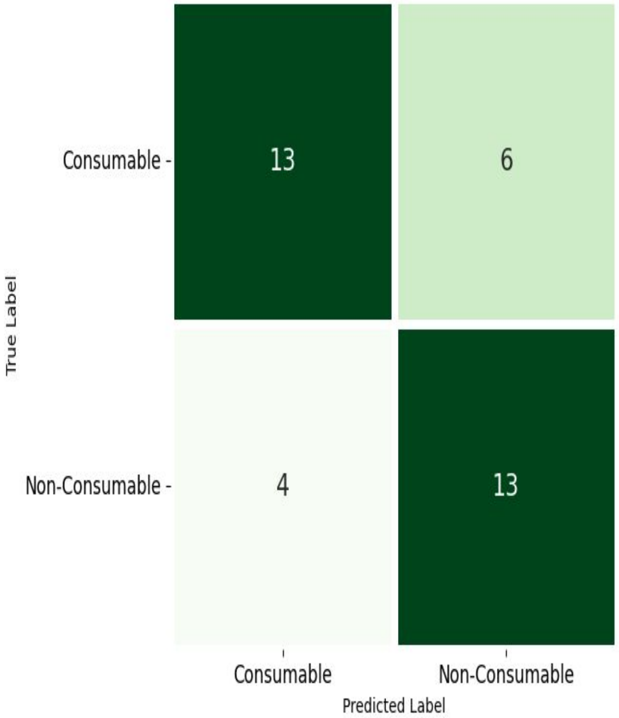
c) Densely-connected-convolutional networks (DenseNet)



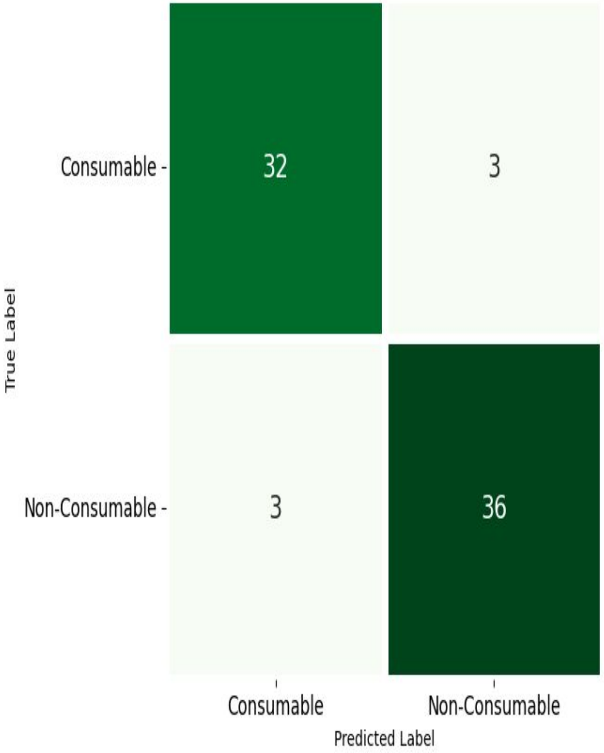
Methodology



Chicken Dataset (HSV)



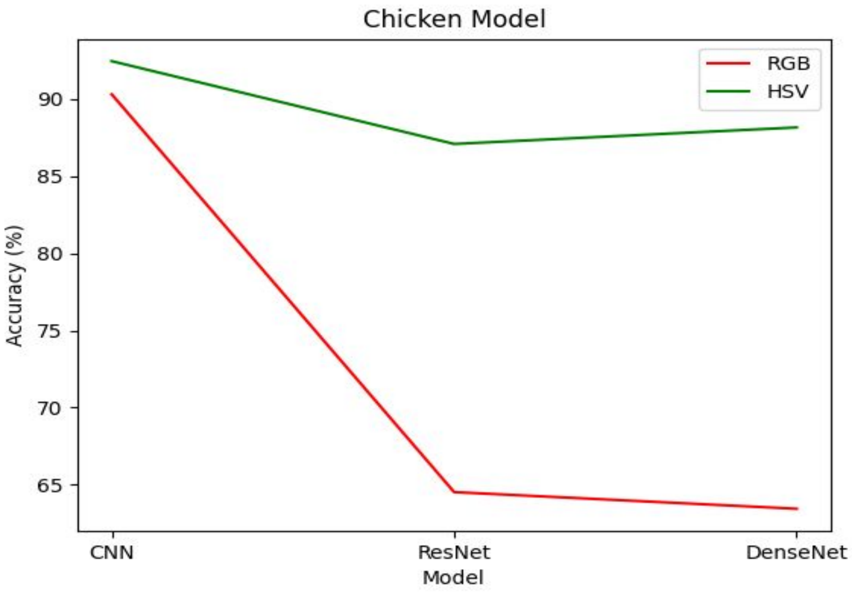
Fish Dataset (HSV)

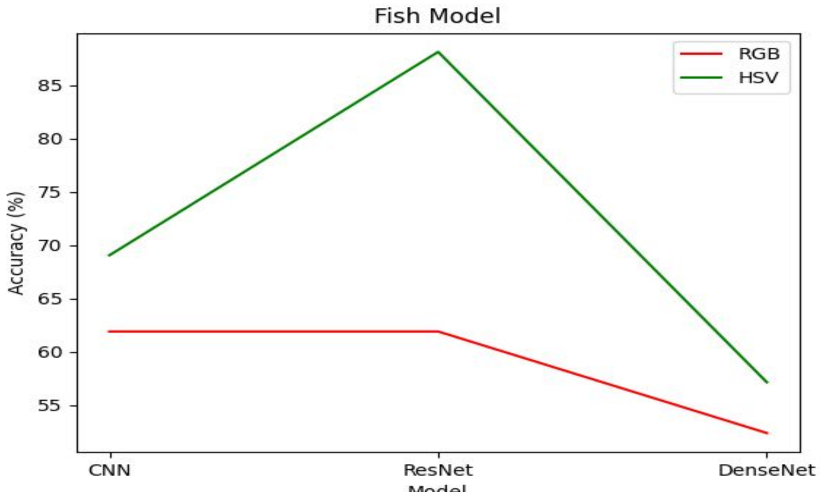


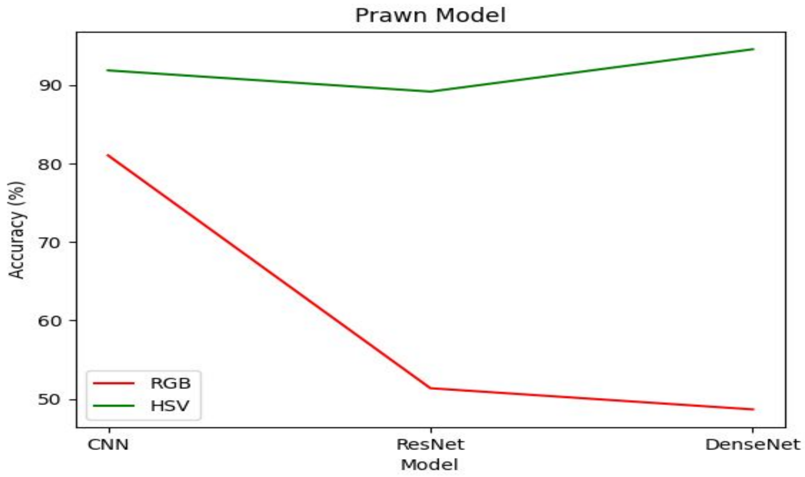
Prawn Dataset (HSV)

Summary

Deep Learning Model’s Summary



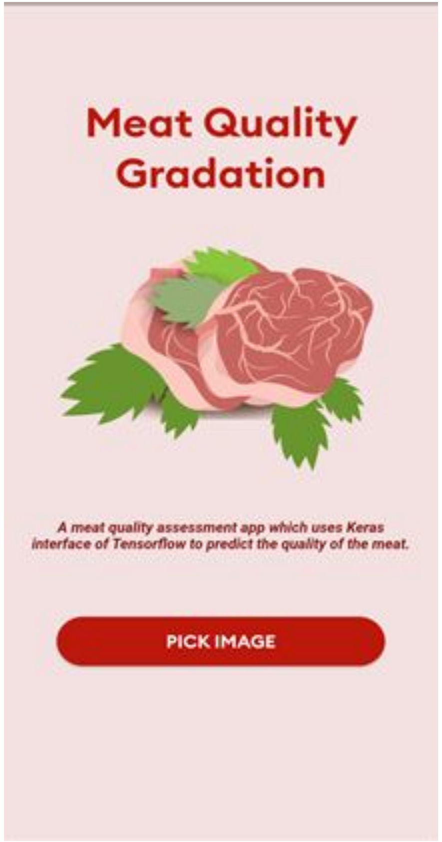


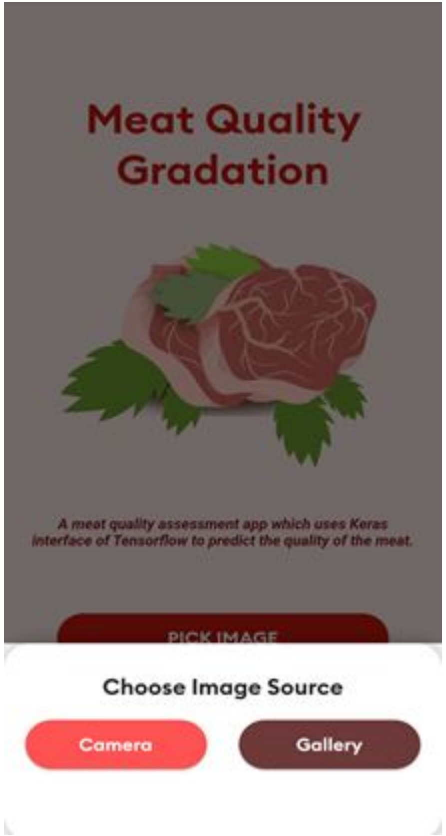


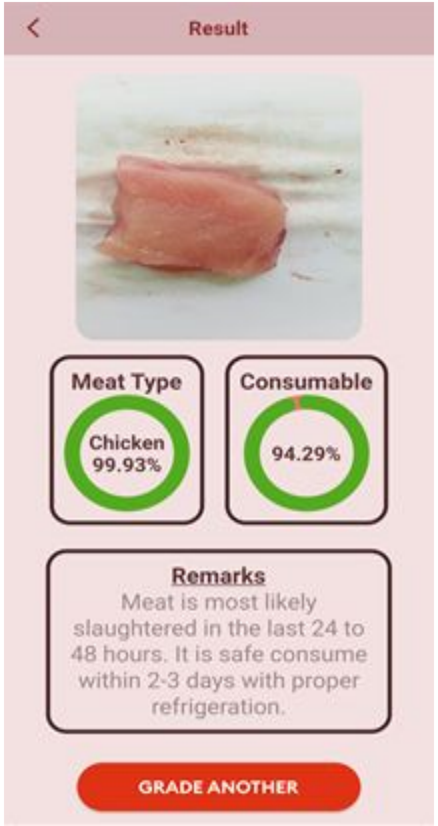
App Development

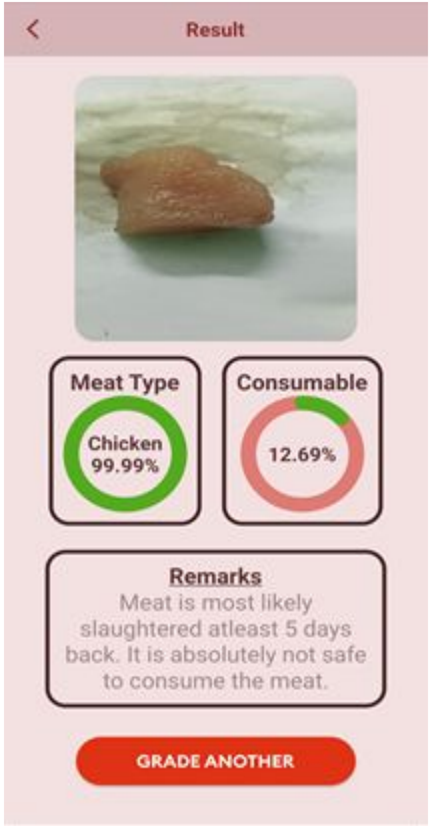
- A mobile application using Flutter framework is developed to implement the idea of the above research.
- It integrates a converted TensorFlow Lite (TFLite) model of the CNN model we designed earlier using the Keras interface of the TensorFlow framework.
- The application allows the user to input an image through either the gallery or camera functionality.
- Once the image is input, the TFLite model is used to predict the type of meat and its consumability.
- Additionally, the application provides a remarks section based on the percentage of consumability predicted by the model.
- The application is not only easy to use but also designed to work both online and offline, making it convenient for users who may have limited access to the internet.

App Interface









App Interface

App Video Will Be Here

Conclusion

- We observed for all the datasets Machine Learning as well as Deep Learning models gave better accuracy in HSV color space than RGB color space.
- Machine Learning models like Random Forest gave the best accuracy of 90% in Chicken Dataset. Whereas, Deep Learning models like CNN gave best accuracy of over 92% in the same dataset.
- On average, deep learning models like CNN and DesNet used for the above problem provided better accuracy than the machine learning models.
- It is important to note that deep learning models are particularly effective for image-related tasks, such as object recognition and classification, due to their ability to automatically learn complex features and patterns from large datasets.
- The images used in this study were captured on a white background. However, it is possible that the results could differ if images were taken on a colored background instead.
- To conclude, artificial vision and deep learning is a reliable technique, and it has shown its efficiency in many applications related to meat assessment.

Future Work

- Exploration of more complex deep learning models which are commonly used for image classification and can be efficiently incorporated into low-end devices such as mobile phones or Raspberry Pi's.
- Improvement of the model which predicts the type of meat. While this model is effective in most cases, it is not always accurate as per our tests.
- Making the app connected to the cloud and incorporate reinforcement learning into the app, which would allow the model to rectify it’s output and improve the learning model based on user feedback. This approach would enable the app to continuously improve its accuracy and better meet the needs of its users.
- Incorporate additional features such as nutritional information and recipe suggestions based on the type and quality of the meat.

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