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DEEP CNN MODEL FOR PREDICTING SHELF LIFE OF FRESH FRUITS AND VEGETABLES USING TEMPERATURE SIMULATION DATA FOR OPTIMIZED TRANSPORT AND STORAGE

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ABSTRACT

India is one of the largest producers of fruits and vegetables globally, contributing about 14% of global production., a significant portion of this produce, approximately 30-40%, is lost due to inefficient storage and transportation systems, resulting in an economic loss of ₹92,651 crores (2018). The objective is to develop a deep learning-based model that uses temperature simulation data to accurately predict the shelf life of fresh fruits and vegetables, ensuring optimized transport and storage conditions. The title refers to a machine learning-based approach, specifically using deep CNN models, to predict how long fresh produce (fruits and vegetables) will remain viable based on temperature data collected during storage and transport. This system helps in making decisions to reduce spoilage and improve logistics. Traditionally shelf-life predictions relied on fixed temperature guidelines, manual quality checks, and general estimations from historical data, often leading to inaccuracies and higher wastage. Traditional systems lack precision and adaptability, resulting in inefficient management of fresh produce, leading to higher spoilage and economic losses during transportation and storage. This calls for a more dynamic approach. Reducing post-harvest losses is critical to ensuring food security, especially in India. Machine learning models can offer precise shelf-life predictions by incorporating real-time data, thereby reducing waste, improving economic returns, and ensuring fresher produce reaches consumers. A deep learning-based model, using a CNN trained on temperature data collected from storage and transport conditions, can predict the shelf life of fresh produce in real-time. This would allow stakeholders to adjust storage temperatures and optimize distribution routes, ensuring minimal wastage. The AI model can also provide alerts for optimal consumption times and transport decisions. This system will significantly improve efficiency and reduce the cost associated with spoilage.

KEYWORDS : Deep learning, Convolutional Neural Network, Real-time data, Machine learning

1. INTRODUCTION

Recently, several studies on the shelf life of bananas and categorization have been conducted using clustering and classification to estimate banana ripeness and shelf life. Good shelf life considers both fruit safety and quality as significant factors. Even so, bacteria have frequently been kept an eye on throughout shelf-life research. The categorization of fruits and the identification of fruit quality are currently the primary objectives of multiple research projects. Recently, sorted peeled pistachios using computer vision and color characteristics. In addition, hyperspectral imaging has been shown in studies to be able to identify strawberry erosion, which may be used in the online sorting method[1]. Deep Learning has recently been used to reliably recognise fruits. Some studies have discovered that using a faster R-CNN architecture in the research allowed it to recognise fruits and provide remarkably accurate detection capabilities. Fruit maturity is a crucial criterion for determining shelf life. In the traditional methods, it is essentially an individual's subjective judgment depending on their level of individual's experience. It is possible to differentiate between both subjective and objective approaches for evaluating the fruit shelf life, each with advantages and disadvantages. This research aims to estimate the shelf-life of Cavendish Banana using object detection methods based on Deep Learning models. The objective is to simplify the efforts and to provide a significantly cost-effective method making it easy to implement and affordable throughout the lifecycle of the food supply chain.India is one of the world's top producers of fresh fruits and vegetables, contributing approximately 14% to the global output. Despite this, the country suffers from immense post-harvest losses—estimated at 30-40% of total produce—due to poor infrastructure, inefficient transport systems, and improper storage conditions. These losses amount to an economic loss of nearly ₹92,651 crores annually. Key factors like temperature control during transportation and storage play a vital role in determining the shelf life of these perishable goods. Traditionally, shelf life has been predicted using generalized guidelines, which lack precision, resulting in spoilage and waste. With growing demand for fresh produce in both domestic and international markets, optimizing transport and storage systems has become crucial for reducing food wastage and improving food security. Advanced technologies like Deep Convolutional Neural Networks (CNN), coupled with temperature simulation data, have the potential to transform the way we manage and predict the shelf life of fresh produce. Deep CNN models can analyze temperature patterns during storage and transportation to predict the shelf life of fruits and vegetables with great accuracy. By integrating real-time temperature data, these models help optimize storage conditions, reducing spoilage. The application extends to supply chain optimization, where transport decisions can be tailored to ensure minimal loss, enabling better logistics management and food security.

2. LITERATURE SURVEY

The goal of the paper [2] was to detect intrinsic features of fruits such as internal defects, bruises, texture, and color and classify fruits according to their remaining useful life (RUL). The study uses the data of 'kesar' mango [3]. It uses thermal imaging to determine the intrinsic values of fruits in terms of temperature. Furthermore, a transfer learning approach is combined with thermal imaging techniques to enhance the accuracy of fruit shelf life prediction. The study compares three lightweight CNN-based models, namely SqueezeNet[4], ShuffleNet[2], and MobileNetv2[5]. The results demonstrate that the highest achievable accuracy of up to 98.15% is obtained. It is also observed in the study that using thermal images resulted in a significant reduction in training time. In the paper [6], the aim is to predict the ripeness level and CO2 respiration rate (RRCO2)[7] of the 'kesar' family of mangoes using Artificial Intelligence. To achieve this goal, The study uses a deep learning algorithm that was trained on 1524 images of the fruit. The data used was divided into four classes: 'unripe', 'early-ripe', 'partially-ripe' and 'ideally-ripe'. In progression to this, the research correlates 'RRCO2' and the ripeness level of the Mango. The prediction accuracy using 'VGG-16[8]' on the training dataset was 99%, and the test data set was 96.2%. Near-infrared spectroscopy was used in [9] to analyze the quality of apples at different stages. Unfortunately, there are very limited literatures on fruit shelf life prediction. This research is focused on building a real-time, self-learning model that considers changing information from observations made at the unit level of a fruit throughout every step of the supply chain. The research aims to assess how well a self-learning model predicts storage life and how the existing supply chain can be made more efficient. The accuracy of prediction is close to 98.15%. The paper [10] aims to predict the maturity and quality in terms of the shelf life of fruit. The fruit used was a Banana. The study used a total of 2100 images that were divided into 3 classes: ripe, unripe, and over-ripe, with each containing 700 images. Additionally, it used two sets of datasets. Convolutional neural networks (CNN) and AlexNet[11] algorithms were used to achieve the goal, and the study concluded that CNN was a more suitable algorithm for the dataset used in the research, and its highest accuracy obtained was 99.36%. It can be concluded that various methods proposed in the above-mentioned research papers differ from those used in this study. This research involves estimating of shelf life of banana using object detection techniques, namely Faster RCNN and YOLOv5. It compares the performance of both the models on various grounds, while the above methods proposed by different research studies involve VGG-16, SqueezeNet ShuffleNet, MobileNetv2, CNN and AlexNet. With increasing need for sustainability within the food supply chain, the quality control and food monitoring of agricultural commodities based non-destructive testing has gained in valuable interest [12,13,14,15].

3. PROPOSED SYSTEM

The dataset contains time-series information, with columns representing **time intervals** and corresponding **temperature values**. It is likely aimed at predicting a dependent variable, such as lifespan, based on features like time and temperature. The dataset must be structured and include sufficient observations for robust statistical analysis and machine learning modeling.

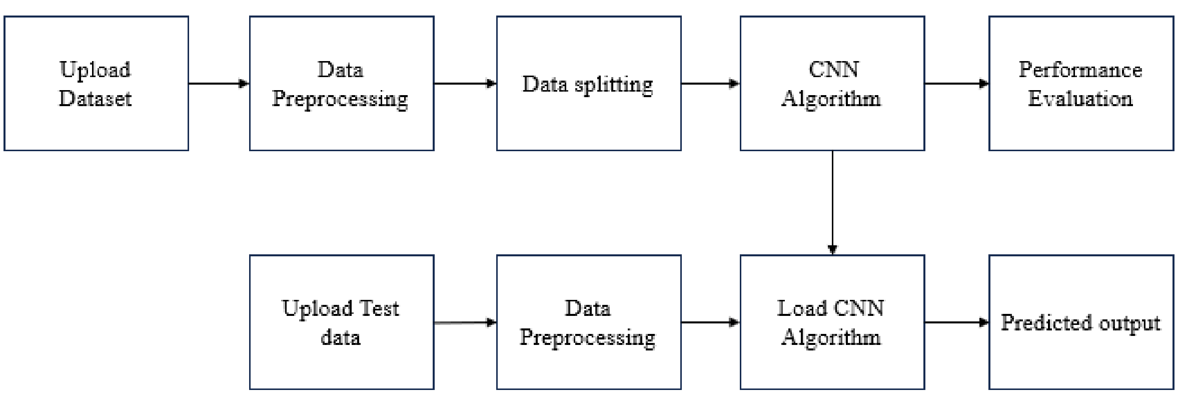

Figure 1 : Proposed Block Diagram

Preprocessing involves cleaning and preparing the dataset for analysis. Steps include handling missing values, normalizing numerical features, and encoding categorical variables. For a time-series or regression task, splitting the dataset into training and test sets and ensuring a balanced representation of all variable ranges is crucial.Analysis of Variance (ANOVA) assesses the relationship between the dependent variable (e.g., lifespan) and categorical independent variables (e.g., temperature). It evaluates whether the means of the dependent variable significantly differ across categories of independent variables, helping identify features with a statistically significant impact.

4. RESULT

Figure 2: GUI

Figure 2 shows that the GUI

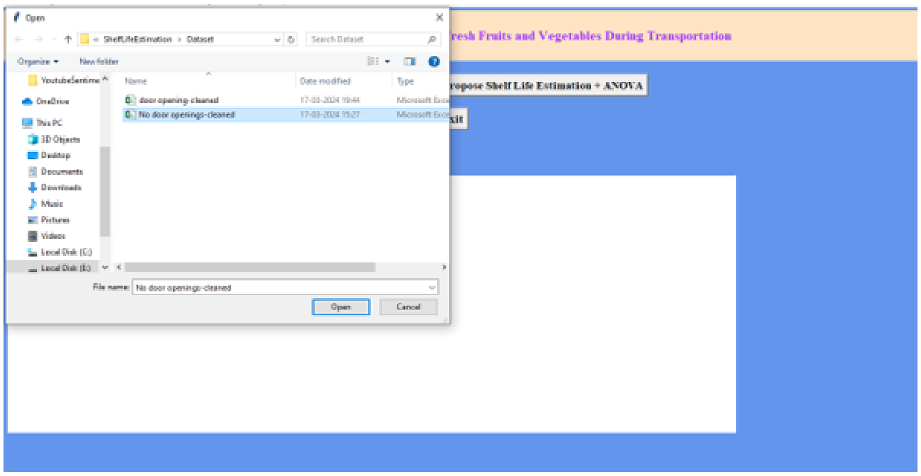

Figure 3: Upload Dataset

In above screen click on 'Upload Strawberry Shelf life Dataset' button to upload dataset

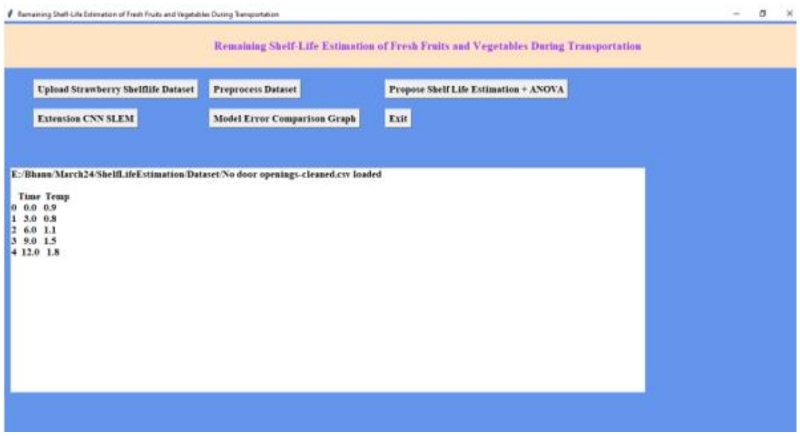

Figure 4: Uploaded Dataset

Figure 4 shows that the In above screen dataset loaded and displaying some values from dataset and now click on 'Pre-process Dataset' button to remove missing values and then calculate RSL for each temperature value and get below output

5. CONCLUSION

Efficient management of fresh produce is a cornerstone of reducing food wastage and ensuring food security, particularly in a country like India, where agricultural production is vast but post-harvest losses remain high. Traditional systems for predicting the shelf life of fruits and vegetables relied heavily on static guidelines, manual inspections, and historical data, which were limited in precision and adaptability. These methods often led to significant spoilage and economic losses, highlighting the need for an innovative approach.The introduction of deep learning-based models marks a transformative step in addressing these challenges. By leveraging convolutional neural networks (CNNs) trained on temperature simulation data, it becomes possible to predict shelf life with high accuracy in real-time. This shift enables dynamic monitoring and adjustment of storage and transportation conditions, minimizing spoilage and improving logistics efficiency.

Furthermore, these models allow stakeholders to optimize routes, reduce costs, and ensure fresher produce reaches consumers. The adoption of AI in shelf-life prediction offers numerous advantages. It provides actionable insights, such as alerts for optimal consumption times and recommendations for adjusting storage settings. Additionally, real-time data integration across the supply chain fosters better collaboration among farmers, distributors, and retailers. By reducing dependency on subjective assessments and static guidelines, this approach ensures a proactive, data-driven management strategy.

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