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AI-Driven Shelf-Life Forecasting for Fresh Fruits and Vegetables Using Temperature-Aware Deep Learning Model

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ABSTRACT

India is one of the largest producers of fruits and vegetables, contributing approximately 14% of global production; however, nearly 30–40% of this produce is lost annually due to inefficient storage and transportation practices, resulting in economic losses of about ₹92,651 crores. Accurate shelf-life prediction is crucial for minimizing post-harvest losses and improving supply chain efficiency. Traditional shelf-life estimation methods rely on fixed temperature thresholds, manual inspections, and historical averages, which lack adaptability and often fail to account for dynamic storage and transport conditions. To address these limitations, this research proposes an AI-driven shelf-life forecasting framework based on a temperature-aware deep learning model. The proposed system employs a Convolutional Neural Network (CNN) trained on temperature simulation data collected during storage and transportation to predict the remaining shelf life of fresh fruits and vegetables in real time. By learning complex temporal patterns associated with temperature variations, the model enables precise shelf-life estimation and supports proactive decision-making. The system allows stakeholders to optimize storage conditions, adjust transportation routes, and issue timely alerts for optimal consumption and distribution. This AI-based approach significantly reduces spoilage, enhances logistics efficiency, and contributes to improved food security and economic sustainability.

Keywords: Shelf-Life Prediction, Fresh Fruits and Vegetables, Deep Learning, Convolutional Neural Network, Temperature-Aware Model, Post-Harvest Loss Reduction, Food Supply Chain, Cold Chain Management, AI in Agriculture

1. INTRODUCTION

The global fruit and vegetable supply chain faces significant losses due to improper handling and suboptimal storage conditions. According to the Food and Agriculture Organization (FAO), approximately

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45% of fruits and vegetables produced worldwide are lost or wasted annually, primarily due to spoilage during post-harvest handling, transportation, and storage. Temperature fluctuations during these phases are a key contributor to shelf life degradation, leading to biochemical changes, microbial growth, and early spoilage. This issue not only affects profitability for farmers and distributors but also contributes to food insecurity and environmental degradation due to wasted resources[1].

Maintaining the cold chain is critical to minimizing perishability. Studies show that even brief exposures to temperatures outside the optimal range can reduce product shelf life by up to 50%. For instance, strawberries, which have a shelf life of 7 days at 0°C, can spoil in just 2 days at 10°C. The economic impact of such degradation is immense. In the United States alone, the annual post-harvest loss of fresh produce exceeds $15 billion. In developing countries, the lack of adequate storage and transportation infrastructure exacerbates the problem, making predictive strategies based on environmental data an essential tool for reducing waste.

Advancements in sensor technologies and IoT-based cold chain monitoring have made it possible to collect high-resolution temperature data throughout the distribution process. These datasets are key to understanding the correlation between environmental conditions and spoilage patterns. However, traditional static shelf life estimation methods fall short in dynamically changing logistics environments. Accurate forecasting models that consider real-time temperature variations are now in demand, especially as fresh produce exporters aim to expand their reach across geographies with extended transit durations.

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.

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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 shelflife 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]. This particularly relates to 'Galia' muskmelons where its climacteric nature results in the contamination of neighbouring fruits when one is afflicted with diseases or pesticides [16].

3. PROPOSED SYSTEM

The proposed system is an AI-driven shelf-life prediction framework that integrates data ingestion, preprocessing, deep learning models, storage layers, and a user-facing dashboard to accurately forecast the shelf life of fresh fruits and vegetables using temperature-aware inputs.

Step 1: User Interaction through GUI Dashboard

The system initiates with user interaction through a graphical user interface (GUI) dashboard, which serves as the primary access point for all stakeholders. The dashboard enables users to upload datasets, monitor prediction outputs, and view alerts related to shelf-life estimation. By providing an intuitive and interactive interface, the system ensures ease of use for non-technical users such as farmers, cold-storage operators, and logistics managers while maintaining operational transparency.

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Step 2: Data Upload Module

The data upload module allows users to submit temperature-related datasets collected during storage and transportation of fruits and vegetables. These datasets may include time-stamped temperature readings, environmental conditions, and produce-specific information. The module supports multiple file formats to ensure flexibility and seamless integration with sensor-based data collection systems, enabling real-time or batch data ingestion.

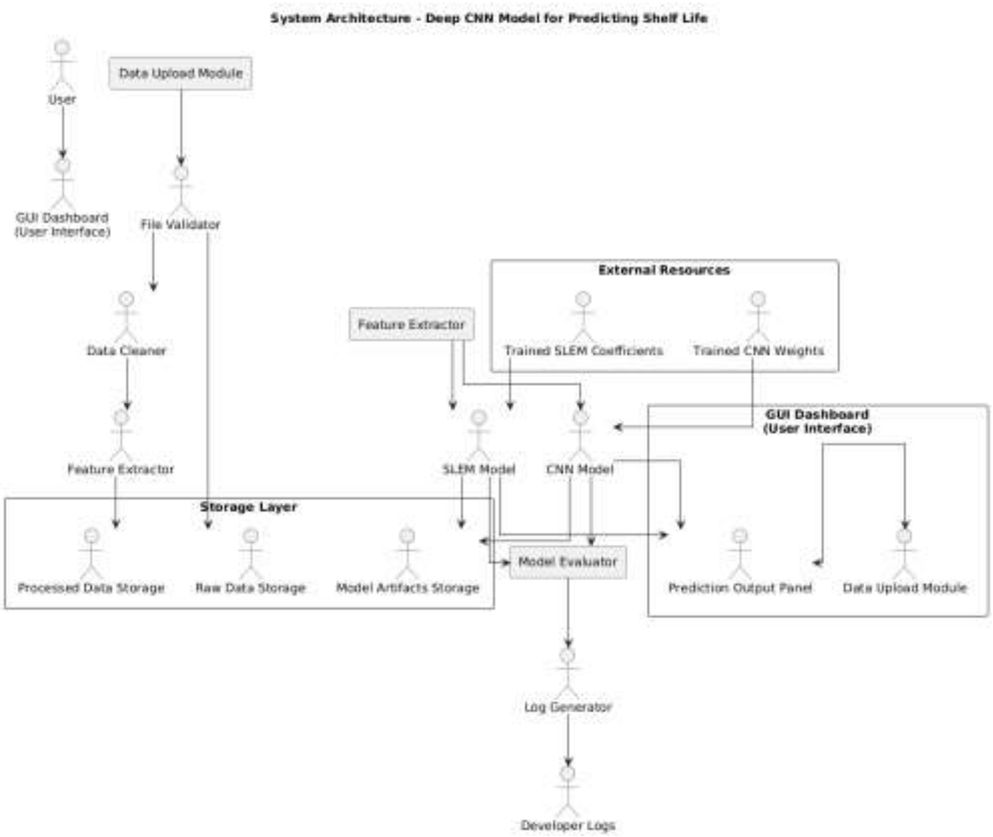

Fig. 1: Proposed block diagram

Step 3: File Validation

Once the data is uploaded, it is passed to the file validation module, which verifies the structural and semantic integrity of the dataset. This step checks file formats, detects missing or corrupted values, validates temperature ranges, and ensures consistency in timestamps. Any invalid or incomplete data is flagged, and feedback is provided to the user through the dashboard to maintain data reliability and prevent erroneous predictions.

Step 4: Data Cleaning

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The validated data is then processed by the data cleaning module to remove inconsistencies and noise. This step includes handling missing values, eliminating duplicate records, smoothing irregular temperature fluctuations, and correcting outliers. Data cleaning enhances the quality of the dataset, ensuring that only accurate and meaningful information is passed to the feature extraction stage.

Step 5: Feature Extraction

In the feature extraction stage, relevant attributes are derived from the cleaned temperature data to capture the degradation behavior of fresh produce. Features such as average temperature, temperature variance, exposure duration, rate of temperature change, and cumulative thermal stress are extracted. These features transform raw sensor data into a structured representation suitable for deep learning and shelf-life modeling.

Step 6: Storage Layer Management

The processed information is managed through a layered storage architecture designed for scalability and traceability. Raw data storage preserves original datasets for auditing purposes, processed data storage maintains cleaned and feature-engineered data for model input, and model artifacts storage securely stores trained CNN weights and SLEM coefficients. This separation improves data management efficiency and supports future retraining and system updates.

Step 7: Integration of External Resources

The system integrates external resources such as pre-trained CNN model weights and trained Shelf Life Estimation Model (SLEM) coefficients. These resources accelerate the prediction process by leveraging previously learned patterns and reduce computational overhead associated with frequent retraining. This integration enhances prediction accuracy while enabling rapid deployment in real-world scenarios.

Step 8: SLEM Model Processing

The Shelf Life Estimation Model (SLEM) processes the extracted features to estimate baseline shelf-life degradation trends. It uses statistical and regression-based learning techniques to provide interpretable shelf-life predictions. The SLEM model complements the deep learning approach by offering stability and explainability in shelf-life estimation under varying temperature conditions.

Step 9: CNN Model Processing

The Convolutional Neural Network (CNN) model receives temperature-aware features and sequential data to capture complex non-linear relationships between environmental conditions and produce spoilage.

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By learning spatial and temporal patterns in temperature variations, the CNN model generates refined shelf-life predictions with high accuracy. This deep learning model adapts dynamically to changing storage and transport conditions.

Step 10: Model Evaluation

Outputs from both the SLEM and CNN models are evaluated using the model evaluation module. This component assesses prediction reliability using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Model evaluation ensures that only validated and high-confidence predictions are forwarded for final decision-making.

Step 11: Prediction Output and Visualization

The evaluated shelf-life predictions are displayed through the prediction output panel on the GUI dashboard. The system presents estimated remaining shelf life, spoilage risk indicators, and actionable recommendations for storage and transportation optimization. This real-time visualization empowers stakeholders to make informed logistics and inventory decisions, reducing wastage and economic loss.

4. RESULTS AND DISCUSSION

The below figure 2 showcases the graphical user interface (GUI) designed for predicting the shelf life of fruits and vegetables. The interface features a user-friendly layout with input fields, buttons, and display areas tailored for entering data related to fruit and vegetable characteristics, such as type, ripeness, storage conditions, or other relevant parameters. The GUI include sections for uploading datasets, initiating predictions, and viewing results, possibly with visual elements like graphs or tables to present shelf-life predictions. The design is intuitive, aimed at enabling users, such as farmers or researchers, to interact seamlessly with the prediction system without requiring extensive technical expertise.

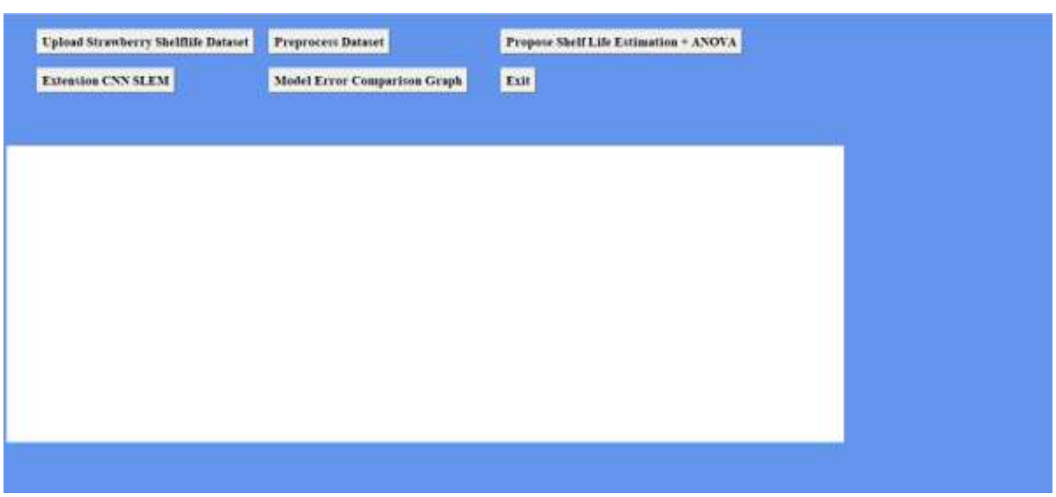

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Fig. 2: GUI of Predicting shelf life of fruits and vegetables

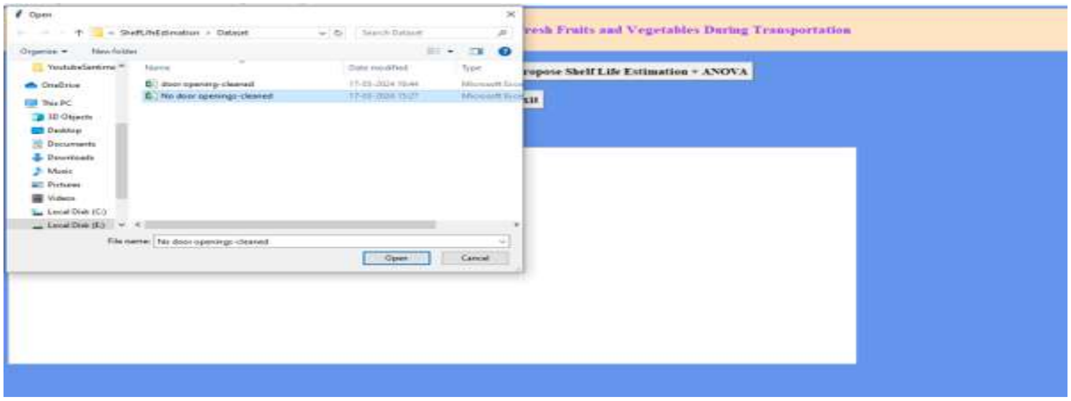

Fig. 3: Uploading the Dataset of fruits and vegetables.

The above figure 3 illustrates the process of uploading a dataset into the shelf-life prediction system. It depicts a specific section of the GUI where users can select and upload a file containing data about fruits and vegetables, such as a CSV or Excel file. The interface shows a "Browse" or "Upload" button, a file path display, and possibly a progress bar or confirmation message indicating the upload status. The figure emphasizes the ease of importing structured data, which include attributes like fruit type, harvest date, or environmental factors, into the system for further analysis.

Fig. 4: Uploaded Dataset in GUI interface.

The figure 4 displays the GUI interface after the dataset of fruits and vegetables has been successfully uploaded. It shows a tabular or structured view of the dataset within the interface, with columns representing attributes and rows corresponding to individual entries. The figure highlights how the GUI

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organizes and presents the uploaded data, making it accessible for users to review before proceeding with shelf-life predictions.

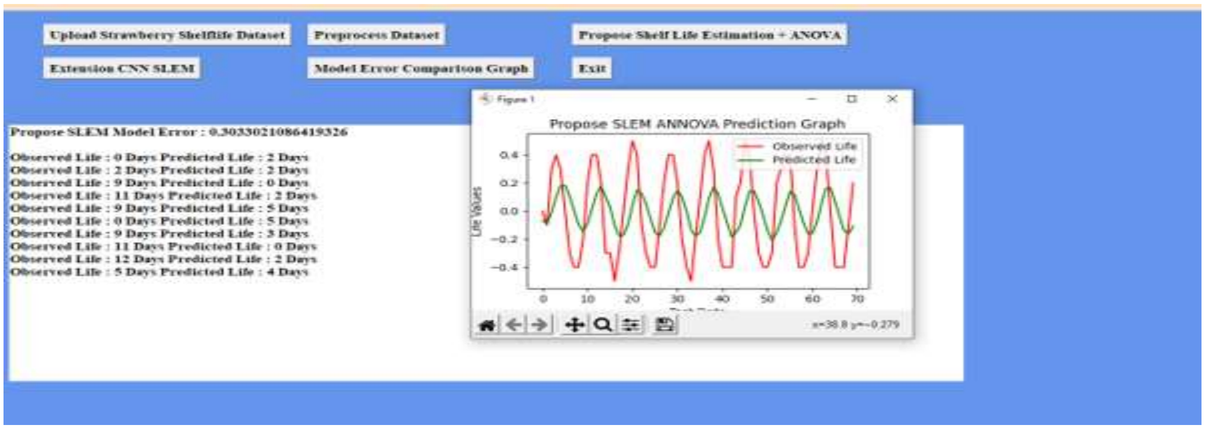

Fig. 5: Prediction of Shelf life using SLEM

The figure 5 shows the Propose Shelf-Life Estimation + ANOVA' button to train ANOVA and then predict future shelf life of fruits and vegetables. In above screen propose model got 30% error rate and in next lines can see Observed or original 'shelf life' and then can see predicted shelf life and can see close difference between original and predicted shelf life. In graph x-axis represents number of test data and y-axis represents shelf life where red line is for Original shelf life and green line is for predicted shelf life. In above graph can see both lines are overlapping with some gap so we can say prediction is little accurate

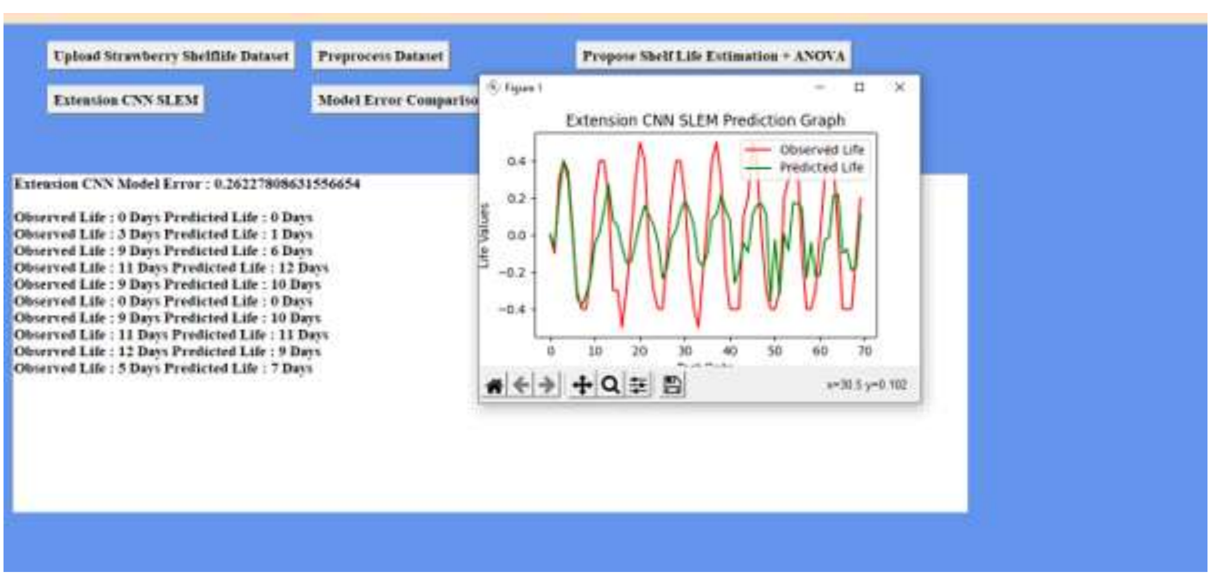

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Fig. 6: Prediction of shelf life using Proposed Extension CNN

In above figure 6 it shows that the extension CNN model got 0.26% error which is lesser than propose algorithm and can see original and predicted shelf life and in graph also can see green and red line overlapping closely.

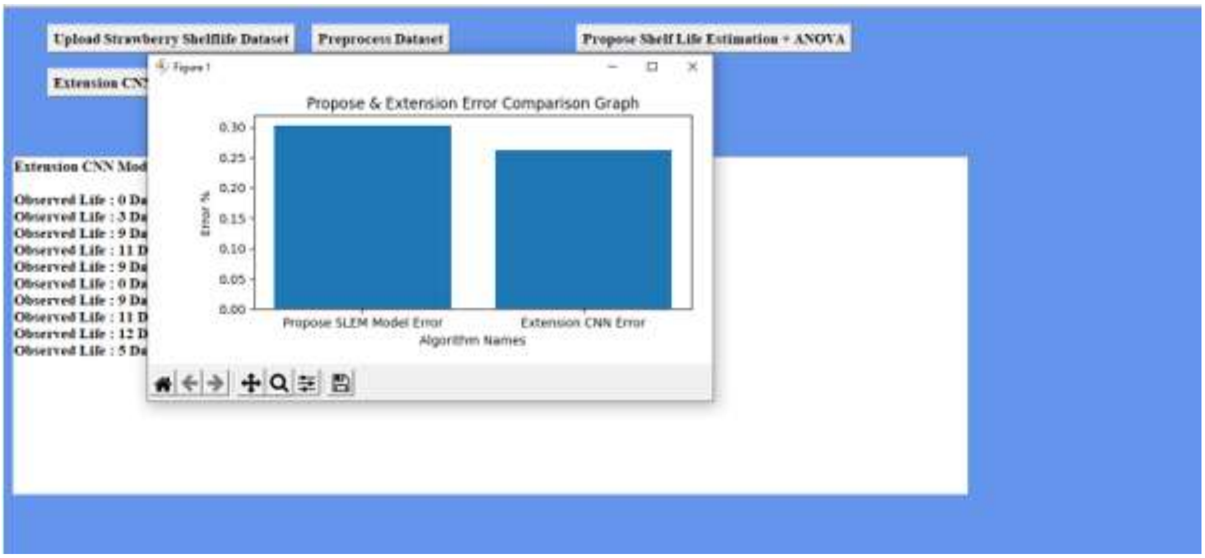
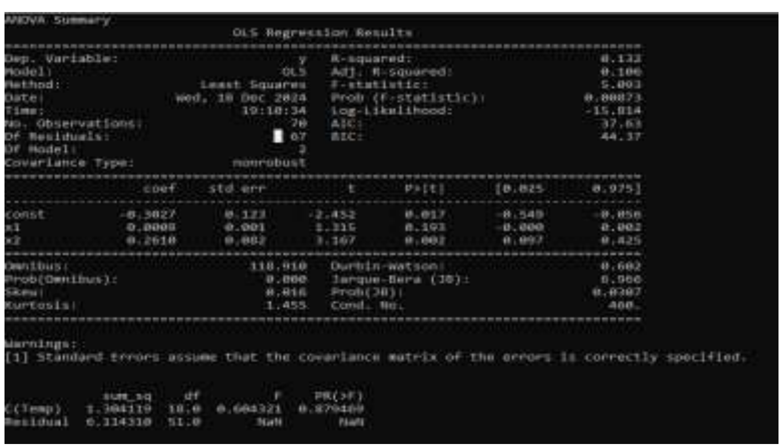


Fig. 7: Comparison graph of SLEM and Extension CNN.

In above figure 7 shows the can see comparison between propose and extension algorithm where x-axis represents algorithm names and y-axis represents model error and, in both algorithms, extension got less error compare to propose ANOVA SLEM algorithm. Similarly, you can upload and test other algorithms.



Extension CNN Model Error: 0.2622780837723077

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- This metric (possibly Mean Squared Error or a similar loss) indicates the overall prediction error of the CNN model. A lower error suggests better performance, though the acceptability of this value depends on the context (e.g., application requirements or benchmarks).

5. CONCLUSION AND FUTURE SCOPE

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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