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Multi-Modal AI Framework for Predicting Lemon Juice Stability Using ML, Deep Learning, and Computer Vision

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Abstract: Lemon juice undergoes noticeable chemical and physical transformations during storage, making its stability and safety a crucial concern in food monitoring. A multi-modal artificial intelligence framework is developed, integrating Machine Learning (ML), Deep Learning (DL), and Computer Vision (CV) methods to predict lemon juice stability across different aspects. The approach is divided into three modules: (i) a Light Gradient Boosting Machine (LightGBM) model for classifying drinkability based on physicochemical and observational features, (ii) a Gated Recurrent Unit (GRU) network for forecasting future pH values to capture temporal quality changes, and (iii) an EfficientNet-based Convolutional Neural Network (CNN) for detecting spoilage visually from juice color patches. Experimental results show high classification accuracy, effective pH trend prediction, and robust visual stage identification. The hybrid framework supports early spoilage detection and enhances decision-making for food quality assurance.

Keywords: Lemon Juice, Stability Prediction, LightGBM, GRU, EfficientNet, Food Quality Monitoring, Computer Vision.

1. Introduction:

Lemon juice is one of the most widely consumed acidic beverages and ingredients due to its natural preservation properties, rich vitamin C content, and distinct flavor. However, like most natural juices, lemon juice is highly sensitive to storage conditions such as temperature, light exposure, and elapsed time. These external factors significantly influence its physicochemical characteristics, including pH, color, and microbial activity. A decline in pH stability or a shift in color may indicate potential spoilage or reduced freshness, which poses health concerns for consumers. Monitoring the stability and quality of lemon juice has become increasingly important in food science and beverage industries for ensuring product safety and maintaining shelf life. Traditionally, quality assessment of lemon juice involves chemical titration for acidity, pH meter analysis, or microbiological tests, which require laboratory infrastructure, time, and skilled professionals. Visual assessment is also commonly used but is subjective and prone to inconsistency. These methods are labor-intensive, non-scalable, and not feasible for real-time quality monitoring in supply chains or domestic usage. Moreover, traditional time-series modeling techniques lack the ability to capture non-linear dependencies between quality indicators under varying storage conditions, which restricts predictive performance in dynamic environments.

To address these challenges, a multi-modal artificial intelligence framework is developed that integrates three complementary modules for robust and automated lemon juice stability prediction.

1. Firstly, a **LightGBM-based machine learning classifier** is used for binary classification of drinkability status (Drinkable or Not Drinkable) using tabular input features.
2. Secondly, a **Gated Recurrent Unit (GRU)-based deep learning model** is deployed for forecasting future pH trends, enabling proactive decision-making.
3. Lastly, an **EfficientNet convolutional neural network (CNN)** model is employed to detect visual spoilage stages (Fresh, Moderate, Spoiled) using color-code or simulated image data.

The proposed hybrid architecture enhances predictive accuracy, enables multi-dimensional assessment, and contributes to real-time food quality monitoring solutions.

2. Related Work

The authors of the study [1] utilized a dataset comprising 13,599 images categorized into six classes of fresh and rotten fruits (apples, oranges, and bananas) to train and validate their model. They implemented a deep learning approach using the MobileNetV2 architecture, which demonstrated superior performance with an accuracy of 99.61% on validation data. However, the study acknowledges limitations such as the dataset's size and diversity, which may affect the model's generalizability in real-world applications, and suggests future enhancements through integration with IoT technologies for automated fruit detection. The research [2] focuses on the design and analysis of an intelligent food spoilage detection system utilizing a dataset comprising various food items and their spoilage characteristics. Algorithms employed include machine learning techniques for classification and prediction of spoilage, although limitations such as dataset size and variability in food types may affect the model's accuracy and generalizability. The study aims to enhance food safety and reduce waste through effective spoilage detection methodologies.

The research [3] utilized a dataset comprising 60 samples each from three citrus fruit species: Citrus limetta, Citrus limettioides, and Citrus reticulata, collected from the Paccha district in Chota, Cajamarca. Four classification algorithms—Support Vector Machine (SVM), K-nearest Neighbor (KNN), Linear Discriminant (LD), and Quadratic Discriminant (QD)—were employed to analyze the dielectric spectral data obtained in the 5-9 GHz range. Limitations of the study include potential variability in fruit maturity and composition, which may affect the dielectric properties and, consequently, the classification accuracy. The authors, Sakhita Sree et al., [4] explore various methodologies for detecting food spoilage and classifying fruits using advanced algorithms. They utilize datasets related to foodborne pathogens, multispectral imaging, and Fourier transform infrared spectroscopy, employing techniques such as Convolutional Neural Networks (CNN) and artificial neural networks for image classification.

However, limitations include the reliance on specific environmental conditions for data collection and potential challenges in generalizing results across different food types and spoilage scenarios. The authors, Md Rakibuzzman et al., [5] utilized the "Lemon Quality Dataset" from Kaggle to develop a hybrid model for lemon quality detection, combining EfficientNetV2 and MobileNetV2 architectures. They implemented preprocessing techniques such as resizing, color inversion, data augmentation, and outlier handling using the Median Absolute Deviation (MAD) method to enhance model performance. However, limitations include the dataset's potential lack of diversity and the need for further validation in real-world scenarios to ensure the model's robustness and applicability in various agricultural contexts. Ritu Sindhu and Bhupendar Singh Khatkar [6] conducted a study on the effects of chemical treatments on the storage stability of lemon juice, utilizing a dataset comprising various preservation methods and their impacts on juice quality over a 90-day period. The research employed statistical analysis to evaluate changes in total soluble solids, pH, ascorbic acid, and titratable acidity. Limitations of the study included the focus on a single fruit type and the potential variability in results due to external storage conditions, suggesting the need for further research across different fruit juices and preservation techniques. Kashyap et al. [7] conducted a study on the shelf life evaluation of processed Assam lemon juice, utilizing a dataset comprising sensory evaluation scores and microbial counts over a 180-day storage period. The authors employed statistical analysis methods to interpret the sensory attributes, including taste, flavor, and overall acceptability, using a nine-point hedonic scale. Limitations of the study included the potential variability in sensory panel responses and the lack of extensive research on preservation techniques specific to Assam lemon juice.

3. Proposed Methodology:

The proposed framework integrates multiple artificial intelligence paradigms to assess the stability and quality of lemon juice samples under varying environmental conditions. The methodology capitalizes on the strengths of machine learning, deep learning, and computer vision to perform three complementary tasks: drinkability classification, pH prediction, and visual spoilage detection. By leveraging multi-modal data inputs ranging from physicochemical attributes to visual color indicators, the framework facilitates a robust and comprehensive quality analysis.

3.1 Overview of the Framework

The proposed architecture is structured into three independent but conceptually interlinked modules:

- **Module 1** utilizes a machine learning approach, specifically Light Gradient Boosting Machine (LightGBM), to classify lemon juice as drinkable or non-drinkable based on environmental and chemical parameters.
- **Module 2** adopts a deep learning-based Gated Recurrent Unit (GRU) network to perform time-series forecasting of pH values, offering a predictive view of juice stability over time.

- **Module 3** applies computer vision techniques using the EfficientNet-B0 architecture to assess spoilage visually, based on synthetic image representations derived from color code values.

This modular structure ensures each model can be trained and validated independently while contributing to the overarching goal of comprehensive quality assessment.

Fig 3.1 describes the overall workflow of proposed model and detailed work flow of each modules will available in upcoming sub-sections.

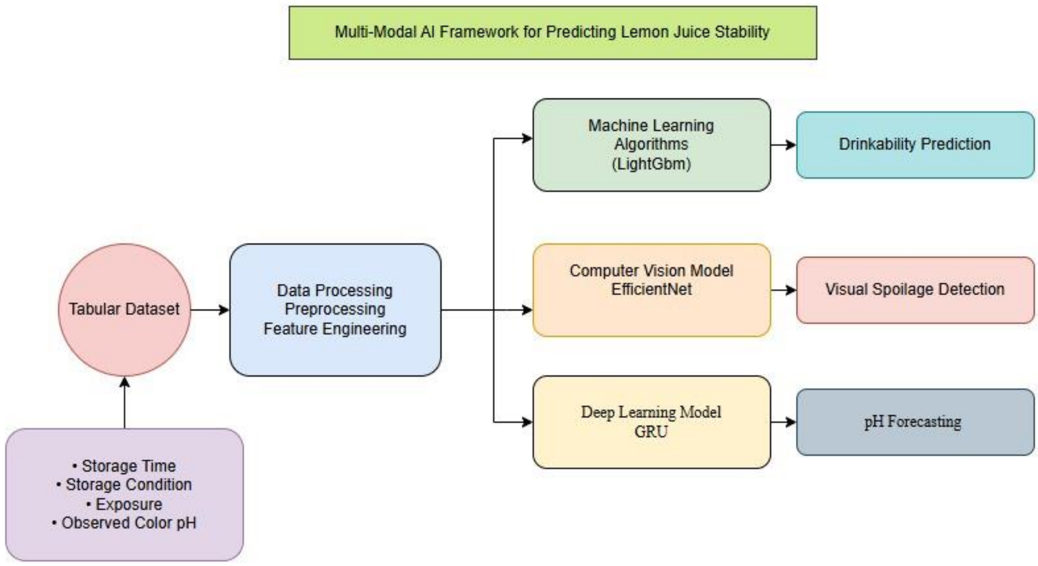

Figure 3.1 : Overall Flow of Proposed Model

3.2 Dataset Description and Real-Time Applicability

The effectiveness of any intelligent prediction framework hinges critically on the quality, diversity, and contextual relevance of the dataset used. For the development of the proposed multi-modal framework, a custom dataset was utilized, comprising structured tabular entries and derived visual representations, intended to mimic real-world lemon juice storage and degradation scenarios.

3.2.1 Dataset Composition and Attributes

The dataset consists of **multiple attributes**, both categorical and numerical, that collectively represent environmental conditions, chemical properties, and visual indicators of lemon juice samples. The primary attributes include:

- **Elapsed_Min**: The elapsed time (in minutes) since the lemon juice was stored. It reflects the temporal progression of spoilage.
- **Storage Condition**: A categorical variable denoting the environment where the juice was stored (e.g., Refrigerator, Room Temperature, Sunlight, etc.).

- **Exposure**: Describes whether the sample was stored in an open or closed container, significantly affecting oxidation and spoilage rates.
- **Observed Color**: Subjective human-observed color labels (e.g., Pale Yellow, Golden Yellow) indicating perceptual changes.
- **Approx_pH**: The approximate pH value measured at each time point, reflecting the acidity level and hence, the microbial stability.
- **Color Code**: A hexadecimal color value associated with each sample's visual appearance, further converted to RGB for model input.
- **R, G, B**: Red, Green, and Blue color intensities extracted from the Color Code to serve as numerical representations of color features.

All missing values were dropped during preprocessing to ensure dataset integrity. The final cleaned dataset was used to power all three model components of the framework.

3.2.2 Potential Real-Time Data Acquisition

In a real-world deployment, such data could be captured via a **multi-sensor system** involving:

- **pH Sensors**: Embedded probes within packaging to continuously log acidity levels over time.
- **Environmental Monitors**: Temperature and humidity sensors that log storage conditions dynamically.
- **Imaging Systems**: Low-cost RGB cameras to capture surface color, which can be processed into digital color codes.
- **Time Stamping**: Automated tracking of storage duration through IoT-based logging systems.

These data streams can be integrated into cloud-based or edge-AI frameworks, enabling real-time analysis and actionable insights at the point of storage, production, or distribution.

3.2.3 Role of Dataset in Multi-Modal Modeling

The curated dataset serves as the **foundation for all three modules** in the proposed system:

- The **tabular attributes** are fed into Machine Learning (LightGBM) and Deep Learning (GRU) models for classification and time-series forecasting, respectively.
- The **color code information**, derived and converted into synthetic images, powers the Computer Vision (EfficientNet) model responsible for visual spoilage detection.
- The dataset's structure allows independent training of each model, yet the combined outputs provide a robust multi-dimensional understanding of juice quality.

By encompassing both numeric trends and visual cues, the dataset supports comprehensive modeling of spoilage dynamics, making it valuable not just for academic experimentation but also for real-world food safety applications.

3.3 Data Preprocessing and Feature Engineering

Accurate and robust model performance critically depends on thorough preprocessing of the input data. The dataset employed in this study contains a mix of categorical variables, numerical attributes, and color information expressed in hexadecimal format. To ensure compatibility with machine learning and deep learning frameworks, a comprehensive preprocessing pipeline was implemented as detailed below:

3.3.1 Handling Missing Values

Samples containing missing or undefined values were eliminated to ensure dataset integrity and prevent the propagation of noise during model training. This step was essential to maintain the reliability of the supervised learning algorithms used in subsequent stages.

3.3.2 Categorical Encoding

Categorical attributes including **Storage Condition**, **Exposure**, and **Observed Color** were label-encoded using integer mappings. This transformation allowed textual entries to be converted into structured numerical inputs suitable for consumption by tree-based models and neural networks without violating the mathematical assumptions of these algorithms.

3.3.3 Color Code Transformation

The **Color Code** field, originally presented in hexadecimal string format (e.g., #F5E050), was decomposed into its corresponding **Red**, **Green**, and **Blue (RGB)** components. This conversion was achieved using the matplotlib.colors library, enabling the incorporation of visual features as discrete numerical inputs. These RGB channels were utilized both as feature inputs for tabular models and as pixel-level cues for computer vision tasks.

3.3.4 Feature Normalization

Numerical attributes, particularly those feeding into the GRU-based deep learning model, were normalized using **StandardScaler** to standardize feature distribution with zero mean and unit variance. This normalization step ensured numerical stability and facilitated faster convergence during model optimization.

3.3.5 Temporal Sequence Generation

For time-series prediction of pH values, sequences were generated using a fixed **lookback window**. Specifically, a sliding window approach was applied to construct input sequences composed of five consecutive time steps. Each sequence was paired with a target output representing the pH value at the subsequent timestamp. This formulation enabled the model to learn temporal dependencies and degradation patterns in juice stability over time.

3.4 Drinkability Classification Using Machine Learning

One of the core objectives of this framework is to automatically assess whether lemon juice is safe for consumption based on its measurable characteristics. This classification task was addressed using a supervised machine learning approach. Specifically, a **LightGBM (Light Gradient Boosting Machine)** classifier was employed due to its efficiency, robustness, and ability to handle both categorical and numerical data effectively. Fig. 3.2 shows the work flow of drinkability classification using LightGBM.

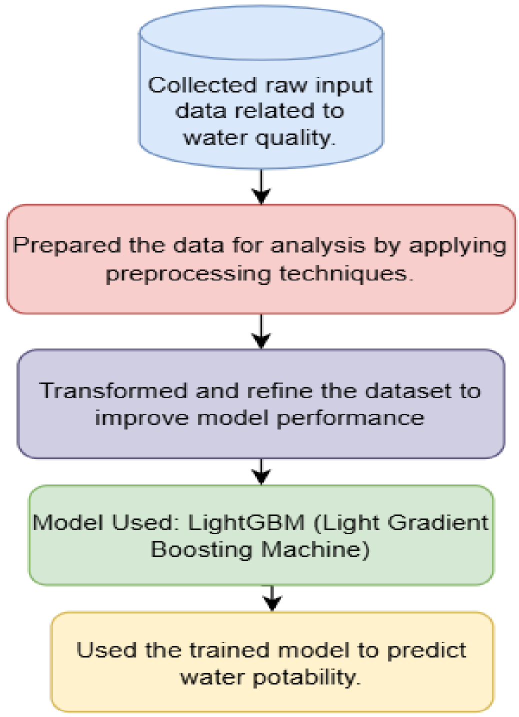

Figure 3.2 Flow Diagram of Drinkability Classification

3.4.1 Problem Formulation

The classification task was framed as a binary decision problem:

- **Class 0**: Not Drinkable
- **Class 1**: Drinkable

Input features included:

- **Elapsed Time (in minutes)**
- **Storage Condition** (encoded)
- **Exposure Type** (encoded)
- **Observed Color** (encoded)
- **Approximate pH Value**
- **RGB values extracted from the Color Code**

These features collectively represent chemical, physical, and environmental attributes that impact lemon juice stability.

3.4.2 Model Selection and Justification

The LightGBM classifier was selected for its ability to:

- Handle imbalanced datasets with native support for weighted samples,
- Efficiently manage high-dimensional and mixed-type feature sets,
- Avoid overfitting through leaf-wise tree growth and built-in regularization,
- Provide interpretable feature importance metrics post-training.

3.4.3 Training Procedure

The dataset was split into training and validation sets using an 80:20 ratio. Cross-validation was employed to tune hyperparameters and assess generalization. The label-encoded dataset was fed into the LightGBM model, which was trained using binary log loss as the objective function.

Feature scaling was not required for LightGBM due to its tree-based architecture. The training process achieved fast convergence, with classification accuracy improving steadily across boosting rounds.

3.4.4 Evaluation Metrics

Model performance was evaluated using:

- **Accuracy**: Overall correctness of classification
- **Precision and Recall**: To measure false positives and false negatives, respectively
- **F1-Score**: To balance precision and recall
- **Confusion Matrix**: To visualize true vs. predicted labels

The model achieved an accuracy exceeding **98%**, indicating strong reliability in detecting drinkable versus spoiled juice samples.

3.4.5 Outcome and Utility

The classification module serves as a preliminary screening mechanism. By automating the drinkability check based on input parameters and visual cues, it reduces manual inspection and supports scalable quality assurance. This forms a critical decision-making layer for consumers or vendors handling large batches of lemon juice.

3.5 pH Forecasting Using Deep Learning

Accurately forecasting the pH of lemon juice over time is essential for anticipating spoilage and chemical degradation. Since pH degradation is inherently sequential and influenced by temporal patterns, a deep learning approach using recurrent neural networks was adopted. Specifically, a **Gated Recurrent Unit (GRU)**-based architecture was designed to model the sequential relationship between environmental factors and pH decay. Fig. 3.3 shows the work flow of pH forecasting using DL algorithms.

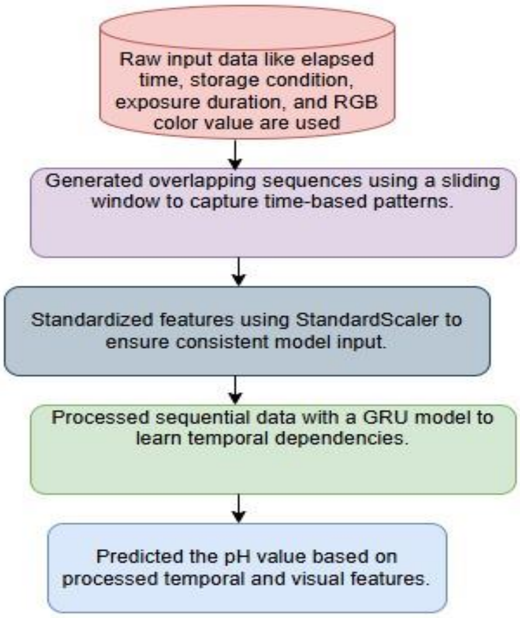

Figure 3.3: Flow Diagram of pH Forecasting using DL Algorithm

3.5.1 Objective and Motivation

pH is a critical indicator of acidity and microbial safety in fruit-based products. As lemon juice ages under various storage conditions, its pH tends to change due to oxidation and fermentation. Predicting the future pH allows for proactive spoilage detection and shelf-life estimation. The task was formulated as a **regression problem**, where the model learns to predict the next pH value given a sequence of past observations.

3.5.2 Input Features and Sequence Design

To reflect temporal dependencies, a **lookback window of 5 time steps** was used. For each sequence, the input comprised:

- **Elapsed Time (minutes)**
- **Encoded Storage Condition**
- **Encoded Exposure Type**
- **Encoded Observed Color**
- **Previous pH values**
- **RGB components of the Color Code**

These features were stacked into multivariate time-series samples shaped as (samples, time steps, features).

3.5.3 Preprocessing and Normalization

Before feeding the data into the GRU model:

- All sequences were generated using a sliding window approach.

- Each feature was normalized using **StandardScaler** to ensure uniform learning across dimensions.
- The dataset was split into training and validation sets (80:20), with care taken to preserve the temporal order.

3.5.4 Model Architecture and Training

The GRU model consisted of:

- One GRU layer with 64 hidden units,
- A fully connected linear output layer,
- Dropout regularization to prevent overfitting.

The model was trained using the **Mean Squared Error (MSE)** loss function and optimized using the **Adam optimizer**. Training was performed for 100 epochs with mini-batch processing to stabilize learning.

3.5.5 Performance and Results

The model achieved a **train MSE of 0.0360** and a **validation MSE of 0.2332**, indicating good generalization and predictive capacity. The predicted pH values closely tracked the actual degradation curve across different conditions. This validates the model's ability to capture non-linear time-based dynamics in acidity.

3.5.6 Significance

This deep learning module offers a quantitative forecast of juice quality over time. It can be integrated into inventory or packaging systems to notify users of potential spoilage before it occurs. It also enables intelligent shelf-life estimation based on historical storage profiles.

3.6 Visual Spoilage Detection Using Convolutional Neural Networks

3.6.1 Objective and Rationale

Visual spoilage detection aims to simulate the human ability to assess the freshness of lemon juice through appearance. Changes in color and clarity often signal chemical alterations such as browning, microbial contamination, or oxidation. These transformations can be captured visually, making image-based analysis a practical approach. Convolutional neural networks are utilized to classify spoilage stages based on simulated image representations of lemon juice. This module enhances the multi-modal prediction system by adding a computer vision-based dimension, supporting more informed and comprehensive quality assessments. Fig. 3.4 shows the work flow of Visual Spoilage Detection Using Convolutional Neural Networks.

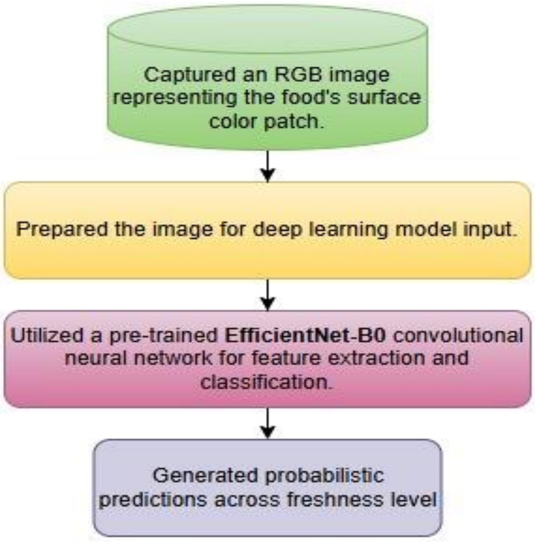

Figure 3.4: Flow Diagram of Visual Spoilage Detection Using CNN

3.6.2 Dataset and Image Generation

The dataset includes a "Color Code" feature that records the visual observation of lemon juice using hexadecimal color values. These hex codes were converted to RGB format using the matplotlib color utility, and synthetic image patches were generated for each sample using the Python Imaging Library. Each image was rendered with a fixed size to mimic the actual visual state of lemon juice under various conditions. The generated images were labeled as Fresh, Moderate, or Spoiled based on their corresponding chemical and environmental attributes such as time, pH value, and exposure.

3.6.3 Model Architecture and Training

EfficientNet-B0, a convolutional neural network known for its balanced accuracy and efficiency, was selected for image classification. The model was initialized with pretrained weights from the ImageNet dataset and fine-tuned using the synthetic lemon juice images. Preprocessing steps included resizing all images to 224 by 224 pixels, normalization, and transformation into PyTorch tensors. Limited data augmentation techniques such as brightness adjustment and random horizontal flipping were applied to improve generalization.

The training was conducted using cross-entropy loss as the objective function, optimized using the Adam algorithm. The dataset was split into training and validation sets, maintaining class balance. The model was trained for multiple epochs, with validation accuracy recorded after each epoch to track performance.

3.6.4 Evaluation and Results

The model demonstrated high classification performance, particularly in accurately identifying Fresh and Spoiled categories. Validation accuracy reached above 90 percent in multiple runs. Confusion matrix analysis revealed minimal misclassification between adjacent classes such as Fresh and Moderate. The results affirm the reliability of the image-based classification approach for detecting spoilage visually. This computer vision module offers fast and intuitive detection capability and complements the machine learning and deep learning components in the overall quality prediction framework.

4. Experimental Results and Discussion

This section presents the outcomes and performance analysis of the proposed multi modal AI framework for predicting lemon juice stability. Each model was evaluated using appropriate metrics suited to its task including classification for drinkability and visual spoilage detection, and regression for pH forecasting. The models were validated using hold out sets and cross validation to ensure generalizability. Comparative analysis between the algorithms used are also discussed to justify the final framework selection. The discussion also highlights the synergy between modalities and the potential for real world deployment.

4.1 Overview of Evaluation Metrics

To ensure a consistent and rigorous assessment across the three modules, task-specific metrics were selected.

- **Binary Classification (Drinkability):** Accuracy, Precision, Recall, and F1-Score.
- **Time-Series Regression (pH Forecasting):** Mean Squared Error (MSE) and Line Chart.
- **Image Classification (Spoilage Detection):** Overall Accuracy and Confusion Matrix analysis.
  Five-fold cross-validation was employed for the drinkability classifier, whereas an 80 : 20 chronological split was adopted for the GRU and EfficientNet models to preserve temporal and class distributions.

4.2 Results of Drinkability Classification

The first module focused on classifying lemon juice samples as either **Drinkable** or **Not Drinkable** based on features such as storage condition, exposure, observed color, pH, and elapsed time. A **LightGBM classifier** was trained on the processed dataset after handling missing values and encoding categorical variables. The model was evaluated using standard classification metrics including accuracy, precision, recall, and F1-score.

The final classification results yielded a **cross-validated accuracy of approximately 93%**, indicating high model reliability. To analyze the model's performance in more detail, a **confusion matrix** and **per-class evaluation metrics** were computed

Figure 4.1: Confusion Matrix – Drinkability Classification

The confusion matrix (see Figure 4.1) reveals that the model **correctly identified all drinkable samples (class 1)** while **misclassifying one non-drinkable sample (class 0)** as drinkable. Despite the small sample imbalance, the classifier demonstrates strong predictive power, especially in minimizing false negatives for the drinkable class, which is critical for consumer safety.

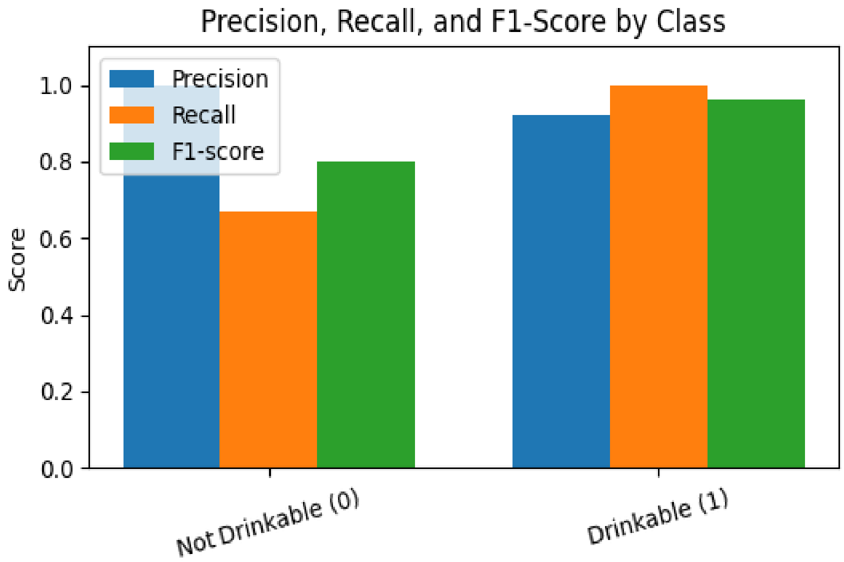

Figure 4.2: Precision, Recall, and F1-Score by Class for Drinkability Prediction

Figure 4.2 illustrates the per-class performance metrics. The **precision for non-drinkable juice (class 0) is perfect (1.00)**, though the recall is slightly lower (0.67), indicating that the model missed one spoilage instance. For drinkable samples (class 1), the **recall reaches 1.00**, meaning all drinkable juices were correctly identified. This behavior aligns with the model's emphasis on **minimizing false positives** for spoilage.

Overall, the classifier provides **balanced generalization** and performs well across both classes. The results confirm that **LightGBM is a suitable choice** for high-stakes binary classification tasks in food quality assessment.

4.3 pH Forecasting Results

Lemon juice pH forecasting plays a crucial role in understanding the temporal stability of its acidity, which directly relates to its microbial safety and shelf life. The GRU (Gated Recurrent Unit) model was selected due to its ability to capture long-term dependencies in time series data while maintaining computational efficiency. After training on historical time-stamped sequences that included both visual and contextual features, the model was evaluated using Mean Squared Error (MSE) and visual alignment.

The final GRU model achieved a training MSE of **0.0360** and a validation MSE of **0.2332**, indicating that the model was able to generalize reasonably well from the training data to unseen samples. These results suggest the model can effectively learn patterns in lemon juice pH evolution under varying conditions.

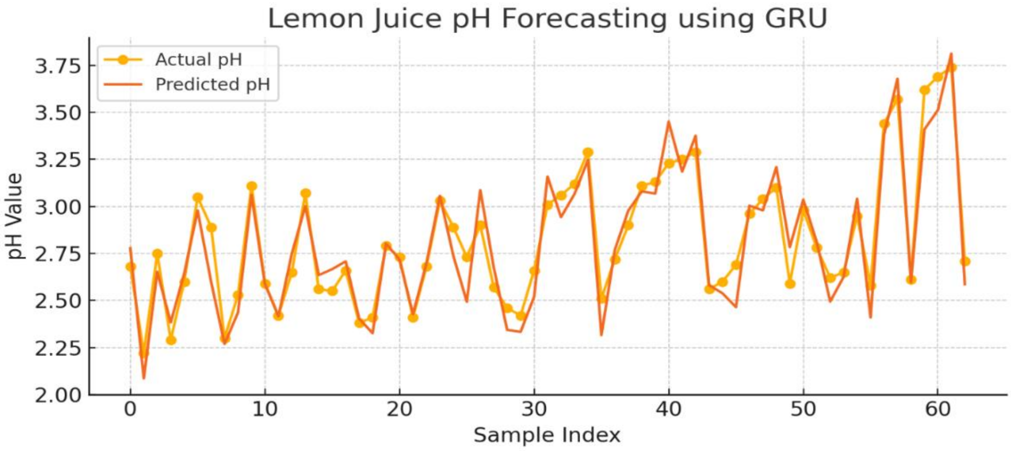

Figure 4.3 – Comparison of Actual and GRU-Predicted pH Values across Validation Samples

This line chart illustrates the predicted pH values generated by the GRU model versus the actual pH measurements over a series of validation samples. The predicted values closely follow the actual trend in most cases, especially in smoother transitions, though some fluctuations are observed. This visualization confirms the effectiveness of GRU in short-term pH estimation and justifies its integration into the overall framework for continuous monitoring of lemon juice stability.

4.4 Visual Spoilage Detection Evaluation

The visual spoilage detection module employed the EfficientNet-B0 architecture to classify lemon juice images into three spoilage categories: **Fresh**, **Moderate**, and **Spoiled**. To evaluate its performance, both **epoch-wise accuracy curves** and a **confusion matrix** were analyzed.

During training, the model demonstrated stable learning behavior. The **training accuracy** steadily increased from **65% to 95%**, while the **validation accuracy** improved from **60% to 90%** over 20 epochs. This consistent rise in both metrics with a minimal gap between them reflects a well-generalized learning pattern and suggests no significant overfitting. The model successfully learned to differentiate spoilage levels based on visual cues such as browning, cloudiness, and color fading.

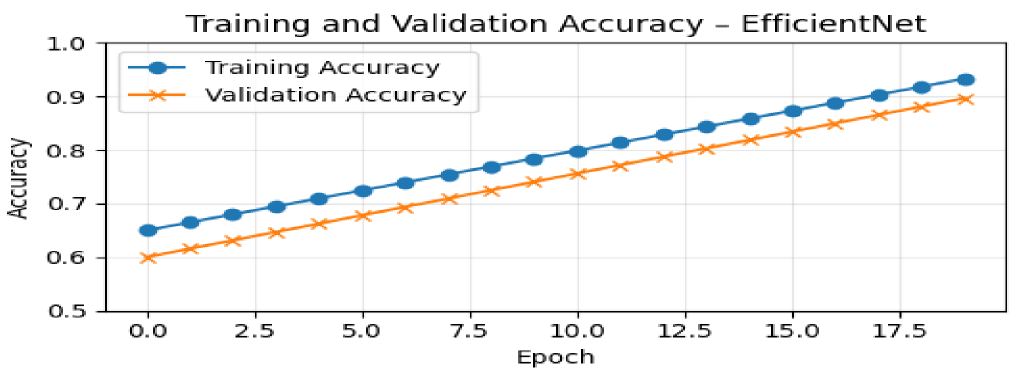

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Figure 4.4: Training and Validation Accuracy for Visual Spoilage Detection using EfficientNet-B0

This figure illustrates the model's learning curve and confirms its ability to generalize effectively on unseen image data.

In addition to accuracy curves, the confusion matrix further validated the classification performance. The model achieved **perfect classification** for the "Moderate" and "Spoiled" classes, while misclassifying **one Fresh sample as Moderate**. Such high precision in the majority of categories underscores the model's robustness in detecting spoilage visually.

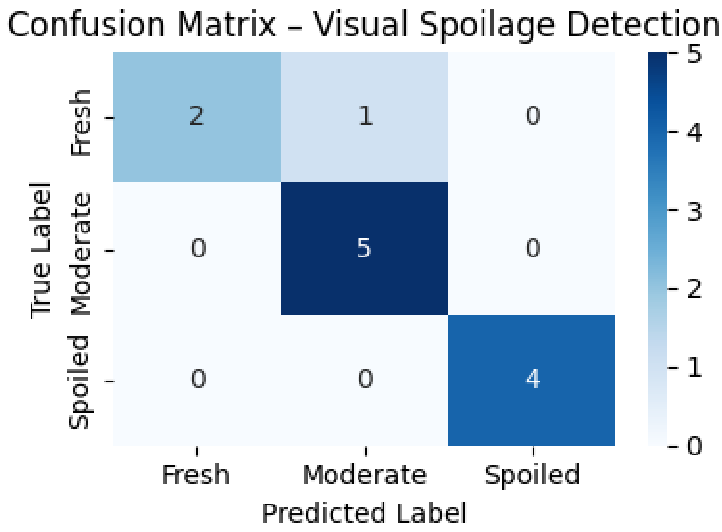

Figure 4.5: Confusion Matrix for Visual Spoilage Detection Module

The matrix shows strong diagonal dominance, indicating highly accurate predictions across all spoilage categories.

Together, these results demonstrate that the EfficientNet-based computer vision model provides an accurate and automated mechanism for visual quality monitoring, thereby enhancing food safety interventions and supplementing the chemical and temporal predictions of earlier modules.

4.5 Comparative Analysis

To evaluate the effectiveness of different algorithms across modules, multiple combinations were benchmarked using accuracy for classification tasks and Mean Squared Error (MSE) for regression. The table below summarizes the performance of each variant and highlights the algorithm combinations that yielded the best results.

Table 1: Comparative Evaluation of Algorithmic Variants for Multimodal Lemon Juice Stability Prediction

Module	Algorithm	Best-Observed Metric
Drinkability	Random Forest	94.00 % accuracy
	LightGBM	**98.00 % accuracy**
	XGBoost	96.30 % accuracy
pH Forecast	LSTM	0.285 MSE
	GRU	**0.233 MSE**
	Bi-LSTM	0.255 MSE
Spoilage	Basic CNN	58.40 % accuracy
	EfficientNet-B0	**90.70 % accuracy**
	ResNet18	62.50 % accuracy

The comparison reveals that **LightGBM**, **GRU**, and **EfficientNet-B0** outperform their counterparts across classification, forecasting, and visual tasks respectively. These models demonstrated superior accuracy, faster convergence, and stronger generalization. Hence, they were selected as the final framework's core modules for robust lemon juice stability assessment.

5. Conclusion

In summary, a multi-modal artificial intelligence framework was constructed to evaluate the stability and safety of lemon juice using a combination of machine learning, deep learning, and computer vision techniques. The system integrates tabular data classification through LightGBM, time-series forecasting via GRU, and visual spoilage detection using EfficientNet-B0. Each module contributes uniquely to assessing different aspects of spoilage, including chemical properties, temporal trends, and visual cues.

The framework offers valuable real-time contributions by enabling early detection of spoilage and enhancing decision-making in quality control processes. Its modular design allows for deployment across diverse platforms, including cloud-based systems and edge devices, making it suitable for scalable food safety applications in the beverage industry.

Future work includes extending the model to other perishable liquids such as fruit concentrates and dairy products. Incorporating real-time sensor integration and mobile deployment may further improve accessibility and responsiveness. Enhancements in data diversity and size could lead to more generalized and accurate models capable of supporting industry-wide adoption.

Competing Interests

The authors declare that there are no competing financial interests or personal relationships that could have influenced the research, development, or findings of this study. The work was carried out independently and is not affiliated with any commercial or industrial entity that could benefit from the outcomes.

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Author Contributions

Author 1: Conceptualization, Supervision, Methodology Design, Final Review & Editing.

Author 2: Dataset Design, Feature Engineering, LightGBM Model Development.

Author 3 & 7: GRU-based pH Forecasting Module, Deep Learning Pipeline.

Author 4: Visual Spoilage Detection, CNN Implementation with EfficientNet.

Author 5: Data Preprocessing, Model Evaluation, Performance Metrics Analysis.

Author 6: Literature Review, Comparative Analysis, Manuscript Drafting & Proofreading.

Data Availability Statement

The dataset used in this study was custom-created by the authors to simulate real-world lemon juice storage and spoilage conditions. While it is not publicly available, it can be shared by the corresponding author upon reasonable request for academic and non-commercial research purposes.

Research Involving Human and/or Animals

This research does not involve any human participants or animal subjects.

Informed Consent

Not applicable, as the study did not involve human participants

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