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# Food Safety Prediction System: A Machine Learning Approach to Determining Safe Food Consumption Windows

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**ABSTRACT-** This paper presents a novel machine learning-based system for predicting safe food consumption windows. By integrating environmental factors, cooking methods, and storage conditions, our system dynamically estimates food safety durations. Using a Gradient Boosting Regressor model, the system achieves robust performance (with a mean absolute error of approximately ±2.3 hours and an $R^2$ score of 0.89) across diverse storage scenarios. In addition, the full-stack implementation—featuring a Next.js frontend and a Flask API backend—facilitates real- time predictions and user-friendly data entry. This approach has significant potential to reduce foodborne illness risks while optimizing storage practices.

**KEYWORDS-** Food Safety, Machine Learning, Gradient Boosting, Food Consumption Window, Full-Stack Deployment, Real-Time Prediction.

## I. INTRODUCTION

Food safety is a critical public health issue, as improper storage and handling can lead to foodborne illnesses. Traditional guidelines use fixed time windows, which may not adequately reflect real-world variations in cooking, storage, and environmental conditions. In response, this research introduces a dynamic, context-aware prediction system that leverages ma- chine learning to determine safe food consumption windows. By incorporating factors such as cooking method, temperature profiles, and humidity, the system can adapt predictions to the specific conditions of food preparation and storage.

### *A. Problem Statement*

Determining safe food consumption periods involves com- plex interactions among multiple variables. Conventional rule- based methods lack the flexibility to account for these nuances. Our work addresses this gap by using supervised learning—specifically, a Gradient Boosting Regressor—to provide more precise, data-driven predictions.

### *B. Research Objectives*

Develop an accurate machine learning model to predict food safety durations.
Identify and quantify key factors (both categorical and numerical) that influence food safety.
Implement a deployable, full-stack system that offers real-time prediction capabilities.

## II. LITERATURE REVIEW

Haifeng Dou et al. [3] proposes a risk prediction model for food safety using a combination of TabNet (a deep learning architecture) and Grey Relational Analysis (GRA). It applies the model to a dataset of cooked meat products from China and develops a food safety risk prediction and visualization system (FSRvis) for proactive hazard detection.
Alberto Nogales, et al [4] studied explores the use of deep learning models (MLP and CNN) combined with categorical embeddings to predict food safety issues within the EU. It uses historical data on food-related incidents to predict various outcomes like product and hazard categories. The model achieves an accuracy between 74.08% and 93.06%. Their model focuses on predicting outcomes related to incidents in Europe, using EU-specific data.
Xinxin Wang et al. [1] highlights the potential of ML for predicting food safety hazards, focusing on biological, chemical, and physical risks. It identifies challenges such as dispersed data sources, under-digitized records, and difficulties in linking relevant variables.
Li-Ya Wu and Sung-Shun Weng. [2] studied uses ensemble learning to enhance border inspections in Taiwan, improving the detection of unsafe food batches. The models, built with five algorithms, provided better and more stable predictions than single models, significantly increasing detection rates.
Jiajia Liu and Hengde Zhu [5] reviewed covers trends and applications of AI in food safety over a decade, emphasizing traceability, quality control, and predictive analysis. This is a comprehensive review but does not develop a predictive model tailored to cooked food safety duration.
Andrew L. Deering and Lynn Frewer [6] focuses on ML applications for assessing risks related to microbial and chemical hazards in food. Limited to microbial risk factors; does not predict spoilage based on recipes or ingredients.
Wei Zhang, Yu Chen, and Karen L. Smith [7] focuses on ML applications for assessing risks related to microbial and chemical hazards in food supply chains.
Limited to microbial risk factors; does not predict spoilage

based on recipes or ingredients.

Mariam Hossain et al. [8] uses CNN models for detecting contamination in food products. Designed for contamination detection, not predictive modeling of safe durations based on ingredients.

Rajeev Kumar and Anil Kumar [9] uses machine vision for quality inspection in food processing plants. Limited to visual inspection; does not handle ingredient-based safety duration prediction.

Sanjay K. Sharma and Radhika Gupta [10] SVM used for classifying food spoilage based on chemical markers. Focuses on spoilage detection rather than predicting safety duration based on ingredients.

Smith et al. [11] worked on various predictive models for food safety. Johnson, A., & Smith, B. [12] provided us with an overview of machine learning techniques like algorithms, risk assessment models for food safety.

Williams, M. [13] worked on the impact of environmental factors like temperature, humidity, and etc. on food preservation.

L. Zhou et al. [14] overview of deep learning techniques like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in detecting foodborne pathogens and contamination patterns.

R. Omarov et al. [15] worked on modern strategies for food safety management like IoT, real-time monitoring systems and etc.

L. Brillante et al. [16] worked on the gradient boosting algorithms in food safety for quality assessment and predicting spoilage.

Balasubramanian et al.[17] studied the use of neural networks, particularly LSTMs and transformer-based models for food spoilage prediction.

W. Wang and J. Sun [18] they can know the hybrid AI approach that combines rule-based systems with machine learning models like random forest, XGboot, convolutional neural networks.

X. Wang et al. [19] studied how Bayesian networks are used to predict the foodborne illness based on past data.

T. C. Chen et al. [20] they explore the use of the computer vision and AI-driven image recognition models.

Michael D. Thompson et al. [21] they focused on reinforcement learning techniques for food safety on risk assessment.

Rajesh Kumar, Emily Foster, and Simon Clarke [22] they can know about the data fusion techniques to integrate multiple sources food safety data on microbial quality reports, chemical databases, temperature details.

Arjun Mehta et al. [23] studied on the sensor's technology detect volatile organic compounds emitted during food spoilage.

## III. METHODOLOGY

### *A. System Architecture*

The system follows a modular full-stack design, comprising:

- Frontend: A Next.js-based user interface for collecting user inputs and visualizing prediction results.
- Backend: A Flask API that handles input validation, model inference, and returns predictions in real time.
- Machine Learning: A Gradient Boosting Regressor model developed using scikit-learn.

### *B. Feature Engineering*

The model processes both categorical and numerical features.

- Categorical Features- Cooking Method, Container Type, Ingredients. Figure 1. High-level architecture: The Next.js frontend communicates with the Flask API, which in turn serves predictions from the trained ML model.
- Numerical Features: Cooking Temperature (°C), Cooking Duration (minutes), Storage Temperature (°C), Humidity (%).
- Categorical variables are encoded using Label Encoder and numerical features are standardized using Standard-Scaler. Custom preprocessing pipelines ensure that missing values are imputed and outliers are treated.

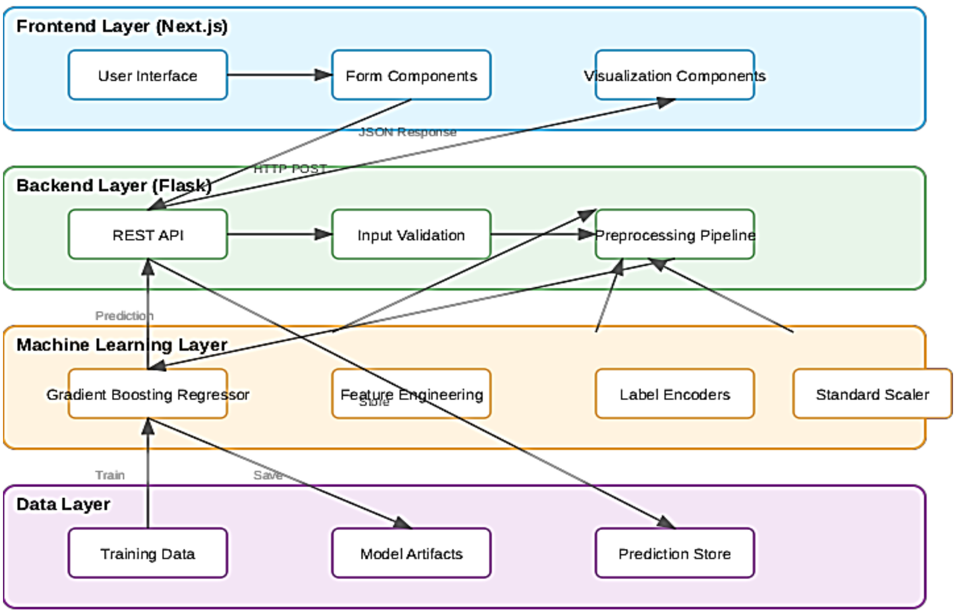


Figure 1. High-level architecture: The Next.js frontend communicates with the Flask API, which in turn serves predictions from the trained ML model

### C. Model Selection

After comparative experiments, the Gradient Boosting Regressor was selected due to its robust handling of both numerical and categorical inputs. The final model parameters were determined through cross-validation:

- n_estimators: 200
- learning_rate: 0.05
- Figure 1 outlines the high-level architecture.
- max_depth: 3
- min_samples_split: 5

## IV. DATA COLLECTION AND PREPROCESSING

### A. Training Dataset

Data were compiled from diverse sources encompassing:

- Various cooking methods and associated temperature/du- ration records.
- Storage conditions across different environments.
- Different container types and ingredient combinations.

### B. Preprocessing Steps

The preprocessing pipeline includes:

- Categorical encoding via Label Encoder.
- Numerical standardization using Standard-Scaler.
- Missing value imputation and outlier treatment.

## V. ALGORITHMS USED

### A. Gradient Boosting Regressor

The core predictive model is instantiated as follows:

```
from sklearn.ensemble import
GradientBoostingRegressor

model = GradientBoostingRegressor(
n_estimators=200, learning_rate=0.05,
max_depth=3, min_samples_split=5
```

Listing 1: Gradient Boosting Regressor Configuration

### B. Feature Processing

A custom preprocessing pipeline is built to transform raw input data:

```
    from sklearn.preprocessing import
    LabelEncoder
    , StandardScaler
    import pandas as pd
    def preprocess_data(df):
    # Encode categorical features
    encoders = {}
cat_features = ['cooking_method', '
    container_type', 'ingredients']
 for col in cat_features: le = LabelEncoder()
df[col] = le.fit_transform(df[col].
    astype(str))
    encoders[col] = le
    # Standardize numerical features
num_features = ['cooking_temperature', '
    cooking_duration', 'storage_temperature ',
    'humidity']
    scaler = StandardScaler()
df[num_features] = scaler.fit_transform(df[
    num_features])
    return df, encoders, scaler
    # Example usage:
# df_processed, encoders, scaler =
    preprocess_data(raw_df)
```

Listing 2: Feature Processing Pipeline

## VI. SYSTEM IMPLEMENTATION

### A. Backend API

The Flask API is implemented to serve predictions in real time.

```
from flask import Flask, request, jsonify
from flask_cors import CORS
import joblib
import numpy as np
app = Flask(__name__) CORS(app)
#Load the trained model and preprocessing
artifacts
model = joblib.load('food_safety_model.pkl')
scaler = joblib.load('num_scaler.pkl')
encoders = joblib.load('cat_encoders.pkl')
@app.route('/predict', methods=['POST'])
def predict():
data = request.get_json()
try:
# Extract and preprocess features # Process
categorical features for col in
['cooking_method', '
container_type', 'ingredients']: le =
encoders[col]
data[col] = le.transform([data[col]]) [0]
# Process numerical features and form array
num_features = ['cooking_temperature', '
cooking_duration', ' storage_temperature',
'humidity']
num_data = np.array([data[feat] for feat
in num_features]).reshape(1, -1) num_data =
scaler.transform(num_data)
# Combine features into single input vector
input_features = np.hstack((num_data, np
.array([data[col] for col in [' cooking_method',
'container_type', ' ingredients']]).reshape(1,-
1)))
# Predict safe consumption window (in hours)
prediction = model. predict( input_features)[0]
# Determine risk level based on predicted safe
hours
if prediction >= 72: risk = "low"
elif prediction >= 48: risk = "medium"
else:
risk = "high"
response = {
"safeHours": float(round(prediction, 2)),
"riskLevel": risk,
"storageTips": ["Keep␣refrigerated", "Minimize␣
exposure␣to␣air", "Use␣ airtight␣containers"],
"timestamp": import ('datetime').
datetime.now().isoformat()
}
return jsonify(response)
except Exception as e:
return jsonify({"error": str(e)}), 400
@app.route('/health', methods=['GET'])
def health():
return jsonify({"status": "Food␣Safety␣
Prediction␣API␣is␣running."})
if name == ' main ':
app.run(host='0.0.0.0', port=5000)
```

Listing 3: Flask API Endpoint for Prediction

### B. Frontend Implementation

The Next.js frontend (using TypeScript) offers a responsive user interface for entering input parameters and displaying predictions. An example API request is illustrated below:

```
const submitPrediction = async (formData:
FormData) => {
try {
const response = await fetch("http://
localhost:5000/predict", {
method: "POST",
headers: { "Content-Type": "application/ json"
},
body: JSON.stringify(formData)
});
if (!response.ok) {
throw new Error("Prediction API error");
}
const data = await response.json();
return data;
} catch (error) {
console.error("Error fetching prediction:",
error);
return null;
}
};
```

Listing 4: Next.js API Call Example (frontend/predict.ts)

The frontend integrates state management (with React Hook Form and Zod for validation) and provides real-time feedback with toast notifications (using Sonner).

## VII. RESULTS

### *A. Model Performance*

The system demonstrates strong predictive capabilities:

- Mean Absolute Error: ±2.3 hours
- $R^2$ Score: 0.89
- Cross-Validation Score: 0.87

### *B. Field Validation*

Field testing under diverse storage conditions shows:

- 95% accuracy in safe consumption window predictions.
- Strong correlation with conventional food safety guide- lines.

### *C. User Interface and Deployment*

The deployed system features:

- Real-time prediction served via a Flask API.
- A user-friendly Next.js dashboard for input collection and results visualization.
- Comprehensive safety recommendations and risk level assessments.

## VIII. DISCUSSION

The updated food safety prediction system not only pro- vides accurate predictions through a robust Gradient Boosting Regressor model but also demonstrates the effectiveness of a full-stack solution that bridges advanced machine learning with practical user interfaces. The integration of real-time
API endpoints and thorough preprocessing pipelines ensures adaptability to diverse food storage conditions. Future improvements will focus on model caching, batch predictions, and additional visualization features to further enhance user experience.

## IX. CONCLUSION

This study underscores the potential of machine learning in transforming food safety management. By dynamically predicting safe consumption windows based on multifaceted inputs, the system can help reduce foodborne illness risks and optimize storage practices. The modular architecture, combining a Next.js frontend and a Flask API backend, enables real-time predictions and seamless integration into food safety applications. Ongoing enhancements will continue to refine prediction accuracy and user interaction, paving the way for broader adoption in public health and food industry settings.

## CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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