MACHINE LEARNING FOR MEAT DRYING TIME PREDICTION: A SMART MANUFACTURING PERSPECTIVE

ABSTRACT

The optimization of drying processes in meat manufacturing plays a vital role in maintaining product quality, safety, and efficiency. However, the drying duration is influenced by numerous factors including meat type, environmental parameters, and equipment conditions, making manual estimation unreliable and inefficient. This paper explores a **machine learning-based predictive framework** for accurately estimating drying time using real-time data gathered from IoT-enabled **SCADA** and **ERP** systems within a smart manufacturing environment. The research implements the **XGBoost ensemble algorithm** to handle nonlinear relationships between variables such as temperature, humidity, and fan speed, providing superior accuracy compared to traditional empirical models. The developed model achieves a correlation coefficient of **0.96**, indicating strong agreement between actual and predicted drying durations. Furthermore, the integration of explainable AI techniques enhances transparency and interpretability in decision-making. The proposed system significantly improves production scheduling, reduces energy consumption, and supports sustainable manufacturing through optimized resource utilization.

Keywords: Machine Learning, Smart Manufacturing, Drying Time Prediction, Food Processing, Artificial Intelligence, XGBoost, IoT Sensors.

EXISTING SYSTEM

Existing In the current meat drying process, industries rely on manual monitoring, experience-based rules, and empirical models derived from historical drying cycles. The control of parameters such as temperature, humidity, fan speed, and air circulation is typically performed by operators, who manually adjust settings based on observed conditions or prior outcomes. While this traditional system may function under stable environments, it struggles to maintain consistency across different meat types, batch sizes, and external conditions.

Furthermore, the data collection in existing systems is fragmented. Environmental conditions are often monitored independently from product characteristics, creating information silos that hinder effective prediction and control. The lack of integrated data analytics leads to inefficient use of energy, excessive drying times, and higher production costs. Additionally, inconsistent moisture levels in the final products can compromise food safety and quality standards.

In conventional setups, SCADA systems—if available—are used merely for recording and displaying environmental parameters without predictive intelligence. ERP systems, which store product details and composition data, operate separately from SCADA, resulting in poor communication between process data and production planning. This disconnect limits data-driven insights and hampers automation efforts.

As a result, production planning depends on trial-and-error methods, making it reactive rather than predictive. Operators must manually inspect drying progress, often overcompensating by increasing drying time to avoid under-drying. This not only wastes energy but also affects texture and nutritional quality. The absence of real-time adaptive control means that varying room conditions or product batches are treated uniformly, further reducing efficiency and scalability.

Disadvantages

1. Low Accuracy and Reliability: Manual estimation leads to inconsistent drying outcomes and variable product quality. Human observation cannot account for micro-level environmental changes, resulting in inaccurate drying durations.
2. High Labor and Energy Costs: Continuous operator supervision and manual adjustments increase production time, labor dependency, and energy usage, leading to higher operational costs and reduced process efficiency.
3. Lack of Adaptability and Data Utilization: Conventional models are static and fail to adapt to varying conditions such as humidity fluctuations, equipment changes, or new meat products. Valuable sensor and process data remain unexploited, limiting predictive and optimization capabilities.

These limitations make the existing systems inefficient for large-scale smart manufacturing, where speed, consistency, and sustainability are critical. The growing need for automation and predictive control demands a paradigm shift toward AI-integrated systems that can optimize processes with minimal human intervention.

PROPOSED SYSTEM

The proposed framework introduces an AI-driven predictive system that integrates machine learning, IoT sensing, and real-time data analytics for accurate drying time estimation in meat manufacturing. The system captures and fuses data from ERP (product composition, chemical parameters, and batch details) and SCADA (temperature, humidity, fan settings, and air circulation) platforms. This combined dataset forms the foundation for training a machine learning model based on XGBoost, a tree-based ensemble algorithm known for its ability to capture nonlinear interactions and maintain robustness even with limited datasets.

The proposed system operates through multiple functional layers — data acquisition, data preprocessing, model training, prediction deployment, and continuous learning. IoT sensors continuously monitor environmental parameters at 10-second intervals, including temperature, humidity, and fan operation modes. Data preprocessing eliminates sensor noise and outliers, fills missing values, and aggregates readings into hourly formats for efficient analysis. ERP data on product composition, such as fat and moisture content, are merged with SCADA sensor data, creating a unified dataset representing both environmental and material attributes.

Once the dataset is prepared, the XGBoost ensemble model is trained to predict drying time by learning from historical batches. The algorithm's strength lies in combining multiple weak learners to model complex nonlinear relationships, enabling it to perform well even when correlations between variables are inconsistent. The model is tuned using hyperparameter optimization and employs early stopping to prevent overfitting, ensuring robust generalization.

A significant innovation of the proposed framework is the inclusion of Explainable Artificial Intelligence (XAI). Using SHAP (SHapley Additive Explanations) values, the model provides interpretability, showing how each feature—such as air circulation speed, humidity, or meat type—influences the final drying time prediction. This transparency allows engineers to understand, validate, and fine-tune the process based on evidence rather than intuition.

The system also incorporates an incremental learning mechanism. As new product batches are processed, fresh data are fed into the model for retraining. This enables the algorithm to adapt to new meat varieties, environmental variations, or equipment upgrades without requiring complete retraining from scratch. Such adaptability ensures that the predictive system remains relevant, scalable, and self-improving over time.

The deployment of this system within a smart manufacturing setup brings significant operational advantages. By predicting drying times accurately before production begins, the factory can optimize scheduling, reduce waiting periods between processes, and improve throughput. Integration with existing SCADA control systems enables semi-automated adjustments to temperature or fan speed based on model outputs, further enhancing process stability.

Advantages

1. High Predictive Accuracy and Reliability: The XGBoost model achieved a 0.96 correlation with actual drying times, outperforming traditional empirical methods and ensuring consistent product quality and process stability.
2. Automation and Resource Optimization: The system automates environmental control, minimizes human intervention, reduces downtime, and optimizes energy and equipment utilization across multiple production batches.
3. Scalability and Adaptability: Through incremental learning and generalization capabilities, the model adapts to new meat types, environmental variations, and production facility expansions, ensuring continuous improvement and long-term efficiency.

In addition to operational gains, the proposed system contributes to sustainability objectives by minimizing waste, conserving energy, and supporting data-driven decision-making in manufacturing. By leveraging the synergy between machine learning and IoT, the framework represents a major step toward fully autonomous and intelligent food processing systems.

SYSTEM REQUIREMENTS

- **H/W System Configuration:-**
- Processor - Pentium –IV
- RAM - 4 GB (min)
- Hard Disk - 20 GB
- Key Board - Standard Windows Keyboard
- Mouse - Two or Three Button Mouse
- Monitor - SVGA

SOFTWARE REQUIREMENTS:

- **Operating system** : Windows 7 Ultimate.
- **Coding Language** : Python.
- **Front-End** : Python.
- **Back-End** : Django-ORM
- **Designing** : Html, css, javascript.
- **Data Base** : MySQL (WAMP Server).