Temperature and Location Monitoring System for Agricultural Transport Using HMM

Abstract

Kenya's small-scale farmers face significant losses due to quality degradation during food transport caused by temperature fluctuations and suboptimal routes. This capstone project proposes a Hidden Markov Model (HMM)-based system to monitor food quality, optimize transport routes, and minimize yield losses. By modeling food quality as hidden states and using temperature and location data as observations, the system provides farmers with actionable insights to maintain quality, reduce transport costs, and protect their livelihoods.

Observations: Measurable Data Used by the Model

The HMM uses two primary data sources collected during transport:

- **Temperature readings**: Captured every 15 minutes via sensors to monitor environmental conditions impacting food quality.
- **Location data**: GPS coordinates or route segment identifiers to track the transport path and correlate temperature variations with specific locations for route optimization.
  These observations enable the model to assess food quality and inform decisions to prevent spoilage.

Type of HMM Problem

The system models food quality (e.g., fresh, slightly degraded, spoiled) as predefined hidden states based on agricultural expertise. The primary HMM task is **learning**, where the model uses historical data (temperature sequences paired with quality outcomes) to estimate the parameters governing state transitions. This learning process refines the model's ability to predict quality degradation based on temperature and location data, enabling real-time monitoring and route optimization for future transports.

Training Algorithm

- **Known Values at the Start**:
  - **Hidden states**: Predefined quality states (e.g., fresh, slightly degraded, spoiled) based on agricultural knowledge.
  - **Initial estimates**: Expert-informed temperature thresholds (e.g., spoilage risk increases above 25°C for perishables).
- **Unknown Values to Be Learned**:
  - **Transition probabilities**: The likelihood of quality state changes (e.g., fresh to spoiled) based on temperature conditions, estimated from historical data.

Parameter Updates

The training algorithm updates **transition probabilities**, which capture how temperature ranges (e.g., low: <20°C, medium: 20–25°C, high: >25°C) drive quality state transitions. For example, the model may learn that temperatures above 30°C increase spoilage probability by 40%. Using historical data, these probabilities are updated via maximum likelihood estimation to adapt to real-world transport conditions.