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Research on Deep Learning-Based Intelligent Prediction Models for Quality Deterioration in Grain and Oil Storage

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Abstract: Stored grain and oil quality are linked to a nation's food security and economic benefits. Traditional grain and oil monitoring methods are mostly performed by practitioners using their experience which can lead to poor timeliness and accuracy of information. Therefore, the purpose of this research is to use deep learning technology to build an intelligent predictive model which helps to overcome the issue of maintaining stored grain and oil quality in complicated storage conditions. The model uses multiple types of monitoring data such as temperature, humidity, and pictures to create an advanced quality deterioration early warning system that can support many different practical storage scenarios. Findings from this research indicate that the model can successfully analyze the complex nonlinear relationships among many of the critical components that affect quality. The findings provide a new technical approach for the intelligent and proactive management of grain oil storage quality.

Keywords: deep learning; grain and oil storage; quality deterioration; intelligent prediction; model

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1. Introduction

Through the implementation of intelligent prediction technologies into the agricultural sector, including an increased use of machine learning and other data-driven approaches, the manner in which grains and oils are stored has dramatically changed, allowing for improvements in overall quality assurance. Storage conditions cause chemical deterioration of grains and oilseeds; however, current storage management methods do not account for this deteriorating process in real-time. Due to their ability to learn complex patterns through feature extraction, deep learning algorithms are optimally designed to utilize time-series and visual data generated from multiple sensor sources located within storage facilities to determine the quality of agricultural products. Utilization of deep learning will ultimately reshape how warehouses manage their product inventories, changing from reactive responses to preventative measures due to the predictions generated by this technology, thus impacting positively on the resilience and capacity of the entire grain storage infrastructure.

2. The Practical Foundation and Technical Support for Intelligent Prediction of Grain and Oil Storage Quality

2.1. Analysis of Core Influencing Factors: Temperature, Humidity and Biological Damage

Micro-biological activity is directly related to temperature and humidity variations within a stored grain pile. Increased moisture and heat will provide an optimum environment for mold and bacteria growth. This consumption of grain nutrients plus the release of heat and moisture from micro-biological metabolism will generate increased temperature in a defined area of a grain pile. The heat generated from this focal point will further cause increased humid and hot conditions in the micro-environment surrounding that specific area. A cycle will occur with increasing temperature and humidity, creating an accelerated rate of quality degradation. Increased humidity and temperature also support increased pest reproduction. In addition to direct loss of grain quality due to pest feeding, pest residues and waste products will create significant contamination of the stored grain. In many cases, the insect presence is concomitant with microbial contamination, which together create a series of irreversible grain deterioration properties such as clumping, discoloration and even the production of toxins. In addition to losing valuable grain nutrients, the damage to stored grains and the resulting increased fatty acid value and also the reduced score for flavor will diminish the nutritional value and commercial aspect of the stored grains [1].

2.2. Mainstream Monitoring Technologies and Data Acquisition Methods

At present, the majority of grain facilities are utilizing digital sensors attached to grain piles to monitor their storage conditions in regard to temperature and humidity. The immediate readings of these sensors provide the first indication of whether or not the storage environment is safe to preserve the grain. Grain facilities also utilize both pest traps and pest detection devices (e.g., electric devices that emit sound) to monitor pest activity for early warning of an impending biological infestation. Some grain storage facilities are also utilizing near-infrared analytical technology via scanning of grain samples for near-infrared data in order to guide handling decisions regarding the ongoing drying process and to accurately predict the quality of grain by assessing the moisture content and level of fatty acids. As a result of using various monitoring technologies outlined above, different types of data will be generated as illustrated in the following table 1, creating a multi-faceted foundation to evaluate the conditions of grain storage.

Table 1. Mainstream Grain and Oil Storage Monitoring Technologies and Their Data Characteristics.

monitoring technology	Main monitoring objects	data format
digital sensor	Temperature and humidity	Time series numerical value
Pest detection device	Pest activity	Event log
Near infrared spectroscopy analysis	Moisture content, fatty acid value	spectral data

These data from different channels, such as the time-series values and event records listed in the table above, form the multi-source information input required for the prediction model. Environmental sensor data depicts the external conditions under which deterioration occurs, while pest information and near-infrared data are more directly related to the physiological changes in the food itself. Effective correlation and integration of various data sources are necessary to provide information materials that depict the complete deterioration chain for subsequent intelligent analysis [2].

3. Current Major Practical Challenges in Grain and Oil Storage Quality Management

3.1. Efficiency and Accuracy Bottlenecks of Traditional Manual Methods

The method of inspecting manually has long been a practice where management employees walk through the storehouse at regular intervals and rely primarily on sight to evaluate the condition of the warehouse and the contents contained within. Their method of determining the quality of stored goods consists primarily of using their sense of smell, touch, and sight; employees will use handheld devices to complete inspections during this time period. This method's inability to provide a thorough inspection or to offer an accurate representation of what happens during an inspection is detrimental for the overall efficiency of the company. The use of manual inspection methods and paper forms to document temperature, pests, and a variety of other environmental and food quality related aspects means management will see all data compiled, summarized, and analyzed at a later date, creating a possible large time gap or disconnect from the date that an employee performed the inspection to the date when management receives the information and assesses it for accuracy or applicable risk factors. Using a fixed inspection cycle creates an internal system for determining risk factors that may arise between scheduled inspection dates and may vary significantly from one employee to the next in how an individual will apply a management strategy for managing any given grain type or warehouse type. For example, the management may rely heavily on the experience of an employee and how he/she may apply their personal biases, creating inconsistencies in how managers perceive the quality of grain.

3.2. Fragmentation Issues in Multi-Source Monitoring Data

Pest-traps continuously monitor temperature, humidity, pest infestation, and gas levels, but typically store this information in individual subsystems. The timestamp of each environmental sensor is not aligned with that of the pest trap image. Therefore, it is not possible to combine data sources into one data repository allowing for simultaneous analysis of the different types of information required to make management decisions. Because management requires multiple software systems to evaluate each of the types of indicators, it also consumes an unreasonable amount of time and energy for the manual comparison of these indicators. Furthermore, during the comparison between indicators, management can overlook significant related indicators. Even where some grain depots have begun to incorporate monitoring systems, there are still potential inconsistencies in the format of the measurement data gathered by the various monitoring devices, further complicating the ability to make horizontal comparisons and conduct historical data mining of data collected during grain storage. This fragmentation of information and systems prevents the evaluation of the grain storage ecosystem's optimal operating conditions holistically and, as a result, it hinders the implementation of a coherent knowledge chain to support multi-dimensional decision-making by management.

3.3. Lagging Risk Alerts and Passive Prevention and Control

Most of the current risk warning systems are based on an alarm system, which is activated when any monitored variable exceeds a predetermined boundary. This method does not consider the fluctuations in the monitored variables (humidity and temperature) that occur during an abnormal event. By the time the alarm notifies the user of a problem in a grain stack (i.e. a localized "hot spot," or area conducive to the proliferation of insects), management has lost valuable minutes rushing to the location for manual inspection and assessment of the situation. The delay in confirming the initial alarm typically means that the only remaining options are fumigating or dumping the affected grain, at which time the grain has generally already been compromised. The passive nature of the current response to a problem not only increases the costs associated with disposal, but also reduces the chance for successful intervention, since the opportunity for intervention has usually passed [3].

3.4. Mismatch Between Advanced Technologies and Grassroots Infrastructure

Many grain depots are located in rural or suburban areas, where network coverage may be unstable, and online monitoring systems that rely on high-speed data transmission face the risk of connection interruptions. The complex steel structure inside the warehouse and the stacked grain piles will further weaken the strength of wireless signals, resulting in poor communication between deployed IoT sensor nodes. The power wiring system of some old-fashioned warehouses is difficult to sustain the continuous operation of a large number of newly added sensing devices, and circuit renovation involves considerable costs and construction periods. Advanced testing equipment usually requires regular professional calibration and maintenance, while grassroots grain depots often lack professional technical personnel with corresponding skills to ensure its long-term reliable operation. Environmental conditions also pose a challenge to the tolerance of precision equipment, as high dust concentration and temperature and humidity fluctuations in grain silos may accelerate equipment aging and affect its measurement accuracy.

3.5. Disconnect Between Prediction Outcomes and Actual Management Practices

Current capability of predictive modelling is only to produce a generalized statement about "risk of deterioration in the next week". It is not possible to convert this statement directly into a set of work instructions for warehousing operations. When there is a risk warning, management must decide for themselves whether to apply management intervention methods such as ventilation, fumigation or food overturning, using their own judgement based on their own experience. There are also significant differences in the format and types of data used by the predictive models compared to the management logs used by daily grain depots, making it very difficult to effectively equate the two when making a decision. Additionally, if the predicted data cannot be unified with established Warehouse Operating Procedures (WOP) and existing constraints in terms of equipment condition and staffing arrangements, then the value of these predictions as guidelines for operation would be diminished. Ultimately, the predictive models and their information are likely to be viewed as independent reference points from the normal operations of the organization, and will not enable an organization to effectively integrate the management loop from warning to action.

4. Practical Application-Oriented Strategies for Intelligent Prediction Model Development and Implementation

4.1. Prediction Model Framework for Multi-Source Data

The objective of the framework which is the predictive model is to enable unified data access and pre-processing through a single centralized location for the collection of temperature and humidity time series, pest monitoring event logs and near infrared spectrum data from grain storage facilities and to create an environment where all data is collected, parsed, and verified using standard procedure. Each item of data will be parsed to ascertain that each has been received, whether or not the data item is a record of pest activity; and that the data item is within the acceptable limits of quality. When the raw data is processed and prepared, it is aligned and associated with all three dimensional views of the same pile of grain by way of the assigned warehouse number, location code and time stamp. A unified three dimensional view of the grain storage facility at a data level will provide the pre-processed and organized data to a deep learning system to discover the relationships between sequences of environmental parameters and sequences of pest activity and spectra of food. A modular design of the entire process will allow grain storage facilities to modify or adjust the method and frequency at which data is accessed and processed.

4.2. Visualized Early Warning and Decision Support Platform

The decision support system provides a user-friendly interface for displaying warehouse-produced data in the format of electronic warehouse maps. This interface provides an intuitive way to view real-time monitoring data for various locations of cargo and risk heat maps created from the risk calculation models. The data panel within the warehouse management system contains the most important indicators that are generated from sensors, pest monitoring locations, and curriculum laboratory reports, giving administrators the ability to compare and see the trends of environmental parameters, biological activity, and curriculum laboratory results on a single screen. The risk warning signals from the risk model appear on the interface with different colors representing different levels of risk, as well as text describing what is contributing to the risk, for example, a risk in a certain area being attributed to a consistent increase in temperature as well as recent cockroach captures. SMS and application notifications are automatically sent to appropriate staff based on the level of warning generated by the model to ensure that critical information is provided promptly. Tools for comparison of historical data and correlation analysis are built into the interface to assist executives in tracking the process of risk formation and assessing the relative effectiveness of mitigation actions taken to address risk in similar circumstances. The design goal of this platform is to transform abstract predictive data into concrete warehouse space management views, providing intuitive basis for making specific decisions on ventilation, fumigation, or flipping operations [4].

4.3. Cost-Effective Integrated Solutions

The economically applicable integrated solution adopts a modular design approach, which allows grain depots to deploy system functional modules in batches based on their own budget and demand urgency. It is recommended to use conventional industrial control computers instead of high-performance servers as the core hardware of the solution. This type of hardware significantly reduces procurement and maintenance costs while meeting the needs of localized data aggregation and model computation. The data collection module is designed to be compatible with temperature and humidity sensors of different brands and communication protocols, as well as pest detection devices, to protect the investment value of existing monitoring equipment in the grain depot. The core algorithm module has undergone lightweight optimization to adapt to the computing power environment of industrial control computers. Its training process can utilize the general model provided by the regional warehousing data center for initialization and local incremental learning. The warning and display module is directly deployed on existing office computers or mobile terminals in the grain depot management area, without the need for additional dedicated display devices. The data flow of the whole system depends on the local area network or industrial bus network deployed inside the granary, so as to avoid dependence on the continuous and stable external Internet connection. Standardized data interfaces are used for communication between modules, facilitating future upgrades and replacements of individual modules based on technological developments or changes in demand.

4.4. Synergistic Workflow Between Prediction Models and Storage Operations

The application promotion work is suitable to adopt a stable strategy of phased implementation. In the initial stage, two to three grain depots with good infrastructure and management foundation are selected as pilot units, and priority is given to those depots that already have basic digital monitoring conditions and have a high acceptance rate among management personnel. The technical team will conduct on-site deployment in the pilot library for several months, with core tasks including completing standardized integration of local sensor data with the system platform, conducting preliminary calibration of prediction models based on historical storage data in the library, and organizing practical rotation training for warehouse keepers and supervisors (see Figure 1). During the pilot operation, a detailed operation log needs to be established to record the triggering points and judgment basis of the system's daily warning, the confirmation results of on-site review by the storage personnel, and the actual operational measures and follow-up effects taken based on the warning. Based on these detailed operation logs and frontline interview records, the promotion team systematically sorted out common operational questions, equipment adaptation issues, and process connection obstacles, and based on this, compiled a troubleshooting guide with illustrations, high-frequency operation scenario video tutorials, and customized easy-to-use operation manuals. The effectiveness evaluation mechanism is based on comparative analysis of multiple production cycles before and after the application of the system. The core evaluation dimensions include but are not limited to changes in storage losses per unit volume of grain, the average time difference from abnormal warning to initial intervention measures, and the planning and accuracy of ventilation and fumigation operations. The evaluation process not only relies on the automatic reporting of the information system, but also requires regular thematic discussions to collect subjective feedback from front-line custodians on system usability and warning credibility. At the same time, it analyzes the equipment stability and model iteration recorded in the technical maintenance log, and combines qualitative experience with quantitative data to form a comprehensive judgment on the practical value and continuous improvement direction of the system [5].

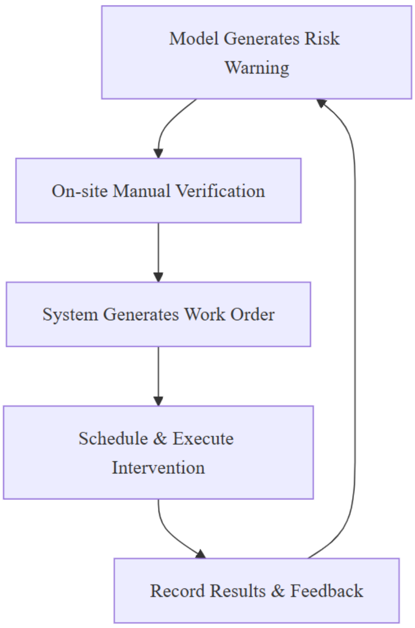

Figure 1. Core process diagram of intelligent prediction and warehouse operation collaboration.

4.5. Application Promotion Pathways and Effectiveness Evaluation Mechanisms

The promotion of applications is best implemented through a phased and steady strategy. In the initial phase, select two to three grain storage facilities with solid infrastructure and management as pilot units, prioritizing those already equipped with basic digital monitoring capabilities and where management personnel exhibit high acceptance. The technical team will conduct on-site deployment for several months at the pilot facilities, with core tasks including standardizing the integration of local sensor data with the system platform, preliminary calibration of predictive models based on historical storage data, and organizing practical training sessions for warehouse keepers and supervisors. During the pilot operation, detailed operational logs must be established to record daily system alert triggers, judgment criteria, confirmation results from on-site reviews by warehouse personnel, as well as actual operational measures taken in response to alerts and their subsequent effects. The promotion team will systematically analyze common operational questions, equipment compatibility issues, and process linkage obstacles based on these detailed logs and frontline interviews, then compile illustrated troubleshooting guides, video tutorials for high-frequency operational scenarios, and customized simplified operation manuals. The effectiveness evaluation mechanism is built on comparative analysis across multiple production cycles before and after system implementation, with core assessment dimensions including but not limited to changes in grain storage losses per unit volume, the average time difference from abnormal alert issuance to initial intervention measures, and the planning precision of operations such as ventilation and fumigation. The evaluation process relies not only on automated reports from the information system but also involves regular thematic discussions to gather subjective feedback from frontline warehouse personnel on system usability and alert reliability, while analyzing equipment stability and model iteration records in technical maintenance logs. This approach combines qualitative experience with quantitative data to form a comprehensive judgment on the system's practical value and direction for continuous improvement.

5. Conclusion

Developing a predictive model that utilizes deep learning represents an important advancement toward data-driven choices in grain and oil warehouse quality management. This research framework utilizes the various types of monitoring to develop a clear picture of the degradation risk factors for these products, allowing managers to eliminate the uncertainty caused by the complexity of the data and gain a better understanding of the early warning signs of deterioration. Collaboratively designing the predictive model together with the warehouse operations provides the opportunity to apply the model's predictions to specific interventions (i.e., ventilation, fumigation) that bridge the gap between technical solutions and management actions. In the future, this research will continue to develop the integration of predictive intelligence with IoT, edge computing, etc., leading to the development of a modern grain and oil storage ecosystem that is more efficient and cost-effective.

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