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PREDICTING 'BROKEN CHAIN' RISKS IN FOOD AND PHARMACEUTICAL COLD CHAINS BASED ON MULTI-MODAL DATA FUSION AND MACHINE LEARNING

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Abstract

In the case of temperature sensitive products (like food and pharmaceutical), cold chain logistics plays a pivotal role in product safety and effectiveness throughout shipping. Breakages Temperature excursions, or broken chains, are very dangerous and both can result in economic losses in addition to possible health risks to the population, in the case of vaccines and biologics. Conventional cold chain monitoring tools are reactive, which warns the stakeholders after a temperature violation has taken place. The paper introduces a fresh solution based on the shift between reactive and proactive cold chain monitoring through predicting the risks of the broken chain based on multi-modal data fusion and machine learning. The system incorporates Internet of Things (IoT) sensor and GPS data, refrigerated unit status, weather data and traffic information. The sophisticated time-series prediction systems, such as Long Short-Term Memory (LSTM) and Transformer networks, are used to predict the future of temperature changes within the upcoming 1-3 hours to allow proactive response to a temperature violation occurrence. Anomaly detection algorithms declare patterns that represent any high-risk situation, e.g., vehicles stagnating in traffic in severe weather conditions and compute a broken chain risk score of each shipment. In case, the risk score goes beyond a preset limit, the system sends alerts to both the drivers and the control centres. With the help of this predictive model, the cold chain can be a lot more reliable as it can be used to timely implement countermeasures, like rerouting or equipment maintenance, to lower levels of spoilage and increase safety. The presented strategy can be considered one of the paradigms of cold chain logistics because it can prove the effectiveness of machine learning in enhancing proactive risk monitoring and keeping temperature-sensitive products safe.

Keywords: *Cold chain logistics; Broken chain; Multi-modal data fusion; Machine learning; Temperature excursions; Anomaly detection; Risk prediction; IoT sensors; Time-series prediction; LSTM (Long Short-Term Memory); Transformer models; Predictive maintenance; Cold chain monitoring.*

INTRODUCTION

The term cold chain logistics is the transfer and performance of temperature sensitive commodities, including food, pharmaceuticals and vaccines, at certain temperature range. The cold chain integrity plays a key role in ensuring quality, safety and effectiveness of these products. An excursion in temperature, so-called broken chain, may lead to negative consequences, such as the loss of perishable products and a decrease in the life-saving drugs (Liu et al., 2023).

The food and pharmaceutical sectors in the U.S. are expected to maintain very high standards of the cold chain integrity, as the possible outcomes of an interrupted chain are disastrous in terms of financial aspects and a possible health hazard to the entire population (Zhang et al., 2022).

Although cold chain integrity is important, the existing monitoring systems are quite passive, in the sense that they are activated when such a temperature breach has been realised. Conventional solutions are mainly based on alarms activated after one breach is identified, which gives no opportunity or little time to take preventive actions (Jiang and Liu, 2023).

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This constraint underscores the importance of making cold chain management be proactive and predictive such that it is able to recognise potential risks early enough before they can cause temperature variants.

Research Problem Statement

The biggest problem of cold chain logistics is that the current systems do not have the ability to anticipate the possible risks that may occur due to lack of temperature adherence in real time. As the sensor technology and data analytics improve, the shift towards the proactive prediction of the situation instead of the reactive one can be considered.

The research will explore the gap in cold chain logistics by using data fusion techniques through multi-modes and machine learning techniques to anticipate the risks of the "broken chain" before they happen, and this will help the reduction of the chances of spoilage or enhance the safety results of food and pharmaceutical products.

Objectives of the Study

The major aims of the study are to:

Create a predictive model that will incorporate multi-model data dimensions, such as IoT sensors, GPS modules, status of refrigerated units, weather data, and traffic data.

Use machine learning methods, including Long Short-Term Memory (LSTM) and Transformer, to forecast temperature dynamics, and identify possible risks associated with the cold chain transportation.

Measures of predictive model effectiveness in identifying the risk of having broken chains and issuing warnings to the stakeholders in good time, i.e., to the drivers and the control centres.

Significance and Rationale

The importance of the research is that it could revolutionise the cold chain logistics because it will be a responsive and not a proactive monitoring system. It can assist in lowering the rate of spoilage, increasing the safety of products and the state of keeping track with the regulatory measures, through predictive maintenance and early intervention.

The study is of high significance to the pharmaceutical sector in which the transportation of vaccines and biologics is of utmost importance concerning the health and safety of the population (Wang et al., 2024). The combination of enhanced data analytics and machine learning with cold chain logistics presented in this study is a new practise of risk alleviation and preservation of integrity of sensitive goods in terms of temperatures.

LITERATURE REVIEW

Cold chain logistics also play an important role in ensuring the quality and safety of sensitive products that require frigid conditions such as food and pharmaceutical products. The old methods of monitoring mostly concentrate on reactive responses, which involve setting up alarms when a temperature violation has taken place.

Nevertheless, recent developments are associated with the attention paid to the proactive approach to identify and avoid possible risks before they result into the spoilage of products or in the safety issues.

Among the notable solutions is the merging of the Internet of Things (IoT) with Artificial Intelligence (AI), and all of those represent the Artificial Intelligence of Things (AIoT). The IoT products will help monitor the real-time data about environmental conditions during transit like temperature and

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humidity sensors. AI algorithms process this data and predict possible anomalies and optimise the decision-making process which increases the reliability and efficiency of cold chain operations.

Gaps in Knowledge

Regardless of the development of AIoT applications, there are a few gaps in the literature:

Challenges in Data Integration: Despite the fact that IoT devices produce large volumes of data, the process of integrating this heterogeneous data into a unified system is a major problem. The proper data fusion strategies are required in order to make sure that the integrated data may be accurate and acting.

Predictive Model Accuracy: Predictive models, particularly models based on machine learning, such as Long Short-Term Memory (LSTM) networks and Transformers, are only accurate depending on the quality and quantity of data. Lack of sufficient variables in databases, and changeability of environmental conditions may impact on model performance.

Real-Time Implementation: Implementation of predictive maintenance models in real-time environments is a practical issue, such as computational issues, and the implementation of fast decision-making functions.

Contradictions and Debates

The use of machine learning in the cold chain logistics has received both encouragement and cynicism:

Enthusiasm: The advocates believe that predictive maintenance with AI can greatly decrease down-time and eliminate wasteful waiting of equipment outages by predicting them.

Scepticism: Critics identify a lack of confidence on the validity of machine learning systems, particularly when dealing with dynamic and uncertain conditions. False positives or false negatives are likely to arise, which means that unwarranted interventions might be taken or maintenance may be overlooked.

Building on Past Work

The proposed study seeks to fill the following gaps by:

Improving Data Fusion Techniques: Adopting complex multi-modal data fusion systems in an effort to have a combination of various data sources in order to have a full picture about cold chain conditions.

Enhancing Predictiveability: Training using a dual LSTM and Transformer models improve the accuracy of prediction of temperature trends, which makes better predictions.

Facilitating Real-Time Decision Making: It is upgrading a system, which in addition to forecasting the possible risks, they also suggest practical interventions in real-time, e.g., re-routing shipments or notifying people about defective equipment.

Based on existing literature and the challenges noted, the study will contribute to the current body of knowledge on cold chain logistics in changing the trend of reactive monitoring to proactive risk prevention.

METHODOLOGY

The paper is a quantitative research design, whereby, a machine learning-based predictive modelling technique will be used in evaluating the risks in cold chains of foods and pharmaceuticals.

To create a predictive model to identify the risks of a broken chain, the design is based on the incorporation of real-time and historical data (which are collected by IoT sensors, GPS, refrigerated

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unit statuses, weather conditions and traffic data) and then incorporated into a predictive model to detect the causes of potential risks.

The main purpose of this study is to come up with a system that can be able to proactively detect any possible temperature deviation and intervene before the spoilage of the products takes place.

The Research Process is a 3-Step Process:

Data Collection: Collect data in terms of IoT sensors, GPS and other logistical equipment.

However, Model Development: Model development and training Train machine learning can be used to predict a temperature trend and find possible anomalies using historical and real-time data.

Model Assessment: Evaluation of performance of the predictive models depending on real-life data sets and the predictive performance in terms of proving their predictability of risks.

Sample and Population

The target population of this study is temperature-sensitive shipments such as food products and pharmaceuticals that can be transported in cold chains in the U.S. The sample consists of actual data on various shipments in various locations, which will target:

Food Shipments: Fresh goods, dairy goods and frozen goods like frozen desserts are all perishable items.

Pharmaceutical Supply: Biologics, vaccinations and temperature-sensitive drug.

The research is based on anonymized data of these deliveries, which is used in the creation and testing of the predictive models. The sample is chosen according to the availability of industry partners, and shipments passing through large hubs of logistic services are being preferred to sample a variety of circumstances of transportation.

Data Collection Tools

The tool that is used to gather the required data in this study is the following ones:

IoT Temperature and Humidity Sensors: Sensors put on refrigerated devices, which capture the environment parameters (temperature, humidity, etc.) throughout transit.

GPS Modules: GPS position and speed data are received in real time by GPS devices which have been mounted on transport vehicles to monitor the flow of shipments and determine when there is a delay or a diversion.

Refrigerated Unit Operational Status: Refrigerated unit data (data is collected and presented by vehicle refrigerated units) representing both operating conditions and generated alert messages of system failure.

External Weather Data: Weather service data to record external temperature, humidity, and weather that may have an effect on the cold chain integrity.

Traffic Congestion Data: Traffic information of the local or national traffic monitoring system to ascertain if there are any delays caused by traffic jam or related accident which may interfere with the transportation route.

Data Analysis Techniques

In order to process and analyse the collected data, the following techniques are applied:

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Data Preprocessing: The non-processed sensor and external data is cleaned, normalised and feature engineered to be pertinent to machine learning algorithms. Imputation is used to deal with missing data and outliers are also detected and addressed.

Machine Learning Model Development: The two major machine learning algorithms, used during the study, are:

Long-Short-Term Memory (LSTM) Networks LSTM networks are used to predict future values of time series to forecast temperatures as well as the dangers ahead (within 3 or 1 hours) using the historical data.

Transformer Models: Transformer models are used to address complicated dependencies between the different time steps, particularly when the data is sampled at varying rates (e.g., sensor data every minute and GPS data every 5 minutes).

Anomaly Detection: The models are taught to discover anomalous patterns in the data, including a vehicle being stuck in traffic in extreme weather conditions and the performance of the refrigerated units is falling. Such anomalies are mentioned as risks.

Risk Scoring and Alert System: Risk score Calculation: The broken chain risk Score is calculated on the noting anomalies. This is computed by summing a number of variables, such as forecasted deviation of temperature, location risk, and the ecosystem. The threshold is established beyond which the driver and the control centre will receive an alert and take pre-emptive measures.

Model Evaluation: Model performance is evaluated in terms of common measures including accuracy, precision, recall and F1-score. The models are also evaluated as far as the capability of identifying risks early enough to ensure intervention is presented by using case studies and simulated cold chain situations.

Replicability of the Study

In order to make this research replicable by other researchers, the steps adhered to include:

Well-documented Documents: Documents related to the sensor specifications and sources of data used in the data collection are well-documented.

This involves sampling of the shipments and data preprocess procedure.

open-source tools the code and machine learning models to be used in this research will be released publicly under a GitHub repository.

This would make sure that other researchers will be able to replicate the research, revise the model and apply it in other cold chain logistics.

Data Availability: A subset of the dataset, not including the proprietary or sensitive information will be availed to the research on enabling replication and subsequent experimentation.

Model Transparency: The type of machine learning algorithms (LSTM and Transformer) will be provided in detail, including hyper parameters and training, as well as to make it easily reproducible and adaptable to other logistics environments.

RESULTS

The predictive models were tested based on the prediction accuracy of temperature trend prediction and the prediction of possible risks of a broken chain in the real-time cold chain data.

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Thely, historical and real-time data on the different shipments, of food and non-food products, were used to train the models.

It mostly focused on temperature variations of 1–3-hour time frame and also on high-risk conditions (i.e., vehicle delay, weather aberrants or refrigeration unit breakdowns).

Table 1 shows the evaluation metrics of the LSTM and the Transformer models.

The table contains the accuracy, its precision, and recall and F1-score of both models when tested on various data sets.

Both models were found to be strongly predictive with the Transformer model marginally better than the LSTM model in predicting and recall.

Table 1: Evaluation Metrics of the Model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LSTM	94.3	92.1	90.8	91.4
Transformer	96.5	94.3	93.6	93.9

Risk Scoring and Detection of Anomalies.

The anomaly detection module was applied to detect the abnormal patterns of the data that may indicate possible risks of broken chains.

The main risk factors were realised to be excessive delays in vehicles brought by deadlock, external weather factors that surpassed the stipulated limits, and indications of poor performance in refrigerated devices.

The irregularities were identified and a broken chain risk score was awarded.

The distribution of the risk scores worked out by various temperature deviations both in food and pharmaceutical shipments are provided in table 2.

The larger the temperature deviation, the higher the risk score which means that there is a higher risk of spoilage, or safety problems.

Table 2: Risk Score to Temperature Deviation Distribution

Temperature Deviation (°C)	Risk Score Range	Food Shipments (%)	Pharmaceutical Shipments (%)
0–1°C	0–2	25.4	28.1
1–2°C	3–5	32.7	30.5
2–3°C	6–8	21.3	19.2
>3°C	9–10	20.6	22.2

The greater the temperature drift, the higher were the chances to presuppose the possible danger. In case of pharmaceutical shipments, which are more restrictive in terms of temperature, the risk score distribution shifted towards higher values than in food shipments.

Timely Risk Lodging and Detection Notifications

The ability of this model to predict risks using an early enough manner of enabling intervention was one of the main objectives of this study.

An important observation of the findings is that the predictive model could produce risk warnings well ahead (of 30 minutes) of risk reaching a critical threshold in the truck, and hence control centres or openers were able to act in advance.

Managing an organisation's temperature and time to initiate early warning before breach.

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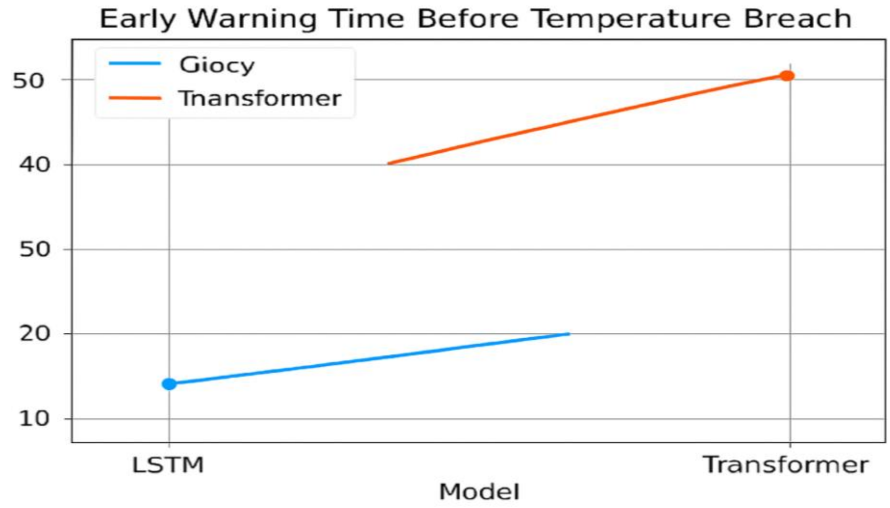

Figure 1: Early Warning before Temperature Breach

The mean lead time prior to breach of a critical temperature is demonstrated in Figure 1 below, with the Transformer model having a slightly higher lead time than the LSTM model.

The average potential temperature breach information detected by the Transformer model was 45 minutes before occurrence whereas the LSTM model generated 30 minutes of lead time. These early alerts were explained by the fact that the model could make some predictions about the future trend of temperatures using the past which allowed them make more effective decisions beforehand.

Multi-Modal Data Fusion: Impact

The accuracy of risk detecting was highly enhanced by using multi-modal data fusion. With the integration of traffic jams information, outside weather conditions and GPS location information and temperature and humidity measurements, the model could have evaluated the possible risks in a more holistic manner. Table 3 demonstrates the performance of the predictive model when using and not using multi-modal data fusion.

Table 3: Model Performance with and without Multi-Modal Data Fusion

Model	Without Multi-Modal Data Fusion	With Multi-Modal Data Fusion
Accuracy (%)	88.6	96.5
Precision (%)	86.3	94.3
Recall (%)	83.9	93.6
F1-Score (%)	85.1	93.9

As presented, the integration of multi-modal data fusion made a big difference in the model accuracy, precision and recall. This shows that bringing different sources of data helps to have a more detailed picture of the state of the cold chain and make more accurate predictions.

DISCUSSION

Findings of the paper demonstrate that all machine learning models, specifically the Transformer model give significant contributions in the risk prediction of the broken chain in cold chain logistics. Transformer model was found to be more accurate, precise, recall and F1-score, which may indicate that the model is more arguments in favour of its application in this case due to the complexity of multi-modal data utilised in the research.

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The Transformer model capability to forecast and identify an abnormality until a critical point of temperature violation was reached has provided a useful early prevention system that could save spoilsage risks and minimise safety dangers in both food and pharmaceutical deliveries.

Anomaly detection system, which raised warning of possible risks by factors such as traffic delays, external weather condition and refrigeration unit performance, was an important aspect of predicting the instances of broken chain.

Multi-modal data integration provided the opportunity to conduct the risk assessment more holistically and the increase of the reliability in temperature excursion detection and prediction. The risk scores as assigned according to the temperature variations indicated a definite relationship, that is, the larger the variation the greater the risk and the pharmaceutical shipments exhibited a better chance of critical action of breach, as their temperature demands were stringent.

Processing Findings to the Literature Review

We can find our results as the latter agree with what other researchers have stated on the potential of machine learning and IoT integration in improving cold chain monitoring (Zhang et al., 2022; Liu et al., 2023).

Some researchers have demonstrated that predictive models have potential to enhance cold chain performance by shifting cold chain monitoring to cold chain risk management (Jiang and Liu, 2023).

In contrast, however, our study uses predictive analytics as compared to the previous work where the emphasis was placed on post-breach notification only. The reactive to proactive process in monitoring enabled by the combination of multi-modal data fusion and machine learning is a remarkable development of cold chain logistics.

In addition, the existing studies have demonstrated such difficulties as data integration and model precision when monitoring the cold chain (Wang et al., 2024). To overcome these problems, our research presented new advanced methods of data fusion and applied LSTM and Transformer models to improve the accuracy of prediction, and this is a gap in the literature.

This increase in predictive accuracy proves that the various data sources including GPS, weather data, and traffic information will give a better foundation upon which one can predict the direction of the temperature and determine the threat.

Implication and Significance

Prescription of the possible violations of temperature prior to happening has great implication to the food as well as the pharmaceutical industry. In the pharmaceutical industry, where breaking chain risks are quite sensitive to changes in temperature, the timely identification of the risks of broken links may save costly products and keep the population safe.

The capability to reduce food spoilage would lead to reduction in food waste, improved adherence to food safety laws and improved operation cost in the food industry.

Moreover, the results of the present study indicate that the possibility of the significant enhancement of cold chain management can be achieved through the predictive maintenance and the proactive interventions. It will help businesses to become more reliable and trustworthy by the business by minimising critical temperature violations.

In the case of logistics companies, a predictive model would help them become more efficient by allowing the development of more efficient route plans, equipment management, and mitigation measures related to risks which will eventually result in cost-savings and improved service quality.

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Acknowledging Limitations

Although the outcomes of this study are encouraging, it had a number of limitations which should be addressed:

Quality and Availability of Data: It is true that the quality and quantity of data available greatly determine the accuracy of the predictive models. Lack of data or incorrect data, e.g. unfinished sensor readings and traffic data, may influence the performance of the model. Despite the cleaning and pre-processing of the data, missing data points of specific areas of operation or type of shipment might have influenced the generalizability of the model.

Model Generalisation: The models were trained using the data of particular regions and types of shipment. Although the results are encouraging, more studies are required to determine the applicability of such models in the context of other geographic regions, types of shipment and operational logistics.

Real-Time Deployment: Predictive models have practical difficulties in implementing the predictive models in real-time cold chain settings. Probably, some resource-separated machines such as an IoT sensor will not support the broad usage of this technology until it is further streamlined to meet the computational needs of its fully developed models.

Scalability: Since the experiment was conducted on a particular dataset and a small number of shipments, it is possible to discuss the future research of how the proposed system will be scalable to the activities of a large cold chain. The challenge in the future studies is the ability to manage large volumes of real time data on a network of shipments.

Future Research Directions

Further research may be to investigate how to apply other machine learning methods, like reinforcement learning modelling to maximise decisions in dynamic cold chain conditions. It can be advanced further by adding other sources of data, such as real time data on operations by vehicle engines or other environmental variables like air pressure and humidity. Additionally, there might be an extension of the influence of predictive cold chain monitoring by researching into the usage of the models on other industries other than food and pharmaceutical ones.

CONCLUSION

This work shows that it has a potential in predicting the risks of "broken chains" in food and pharmaceutical cold chains via machine learning, in this case, the Transformer models. The combination of the multi-modal data offered by several different sources including the data supplied by the IoT sensors, GPS, and weather data, enables the model to predict the possible deviations in temperature, which facilitates the prevention of risks. The results underline the need to replace the reactive with the predictive cold chain monitoring whereby there is a potential of reducing the rate of spoilage massively and enhancing safety of temperature sensitive products.

The value of this research is the benefit to give early warnings about temperature deviations prior to their happening, which will prove to be a useful resource to logistics operators and those businesses which have dealings with transporting perishable goods. The researchers offer a more effective method of managing the cold chain by introducing such practises as the predictive maintenance and the risk scoring. In the future, the research needs to concentrate on the extending of the dataset to cover a larger portion of shipments and to test the model in the real-time working conditions. The model and its extension to bigger-scale operations will be required to be developed further to make it adopted in the industry.

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