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Resilient Pharmaceutical Supply Chain Design Using GRU Forecasting and Grasshopper Optimization Dual Technique

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Abstract

One of the biggest problems facing contemporary medical care is effectively managing pharmaceutical distribution networks and hospital evacuations, especially in times of emergency. This study suggests a novel bi-objective optimization paradigm to handle these issues. The model simultaneously minimizes overall expenses and maximizes patient satisfaction by combining sophisticated artificial intelligence techniques with the Mixed-Integer Linear Programming (MILP) method. The use of Gated Recurrent Unit (GRU) Neural Network (NN) for drug demand forecasting, which permits dynamic resource allocation in emergencies, is a significant advance. To avoid medication shortages, the model also incorporates a dedicated medical supply chain. Supply chain dependability is ensured by considering probabilistic demand patterns and disruption threats to increase system robustness. The solution methodology effectively handles the problem's multi-objective character by combining the e-constraint methodology with the Grasshopper Optimization Algorithm (GOA). The model's usefulness in actual situations is demonstrated by the results in an increase in cost reduction, and it helps in resource allocation and service level. This study offers important insights for improving healthcare logistics on important occasions, improving patient welfare and operational effectiveness, and helps in investigating the current problems medical supply chain management system.

Keywords: Pharmaceutical Supply Chain, Anomaly Detection, Data Integrity, Traceability, Security Incidents.

1 Introduction

Managing the pharmaceutical supply chain has increased in healthcare in recent years, particularly in nations with limited resources and erratic demand (Tsolakis et al., 2023). In addition to being critical for preserving public health, ensuring the reach and sufficient supply of necessary medications is also essential for efficient hospital administration, especially in times of emergency requiring hospital evacuations. To balance conflicting demands for infrastructure capabilities, patient transfers, and medical resources, such crises necessitate quick decisions. Therefore, to save expenses and increase

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patient satisfaction, hospital evacuation logistics must be integrated with pharmaceutical supply chains (Maleki et al., 2024).

Sustaining public health care and reducing shortages or waste of pharmaceutical resources depend on ensuring a timely and sufficient supply of medications (Lotfi et al., 2023). This significance is further highlighted in times of crisis, such as pandemics, when supply chain managers require more precise tools for anticipating and controlling the sharp variations in drug demand (García-Cáceres et al., 2024). trade-offs that make simple modeling more difficult, such as allocating few resources among several demands, making sure that patients who need urgent care receive it on time, and cutting operating expenses. In these difficult situations, it is essential to use creative strategies to increase forecasting accuracy and maximize resource allocation.

There are still large gaps in this field despite tremendous efforts to estimate drug demand and manage the pharmaceutical supply chain (Subramanian, 2021). Demand forecasting has proven difficult with traditional techniques like regression and some machine learning models, especially when faced with abrupt and drastic shifts. Furthermore, a lot of supply chain resource optimization techniques have not been able to keep up with these erratic projections (Joy & Kuruvilla et al., 2025) (Yeo & Jiang et al., 2024) (Patankar & Kapoor et al., 2024). Figure 1 represents the pharmaceutical industry's progress, emphasizing the essential components of every phase, from the manual method of turning medicinal plants into medications to the state-of-the-art production technologies.

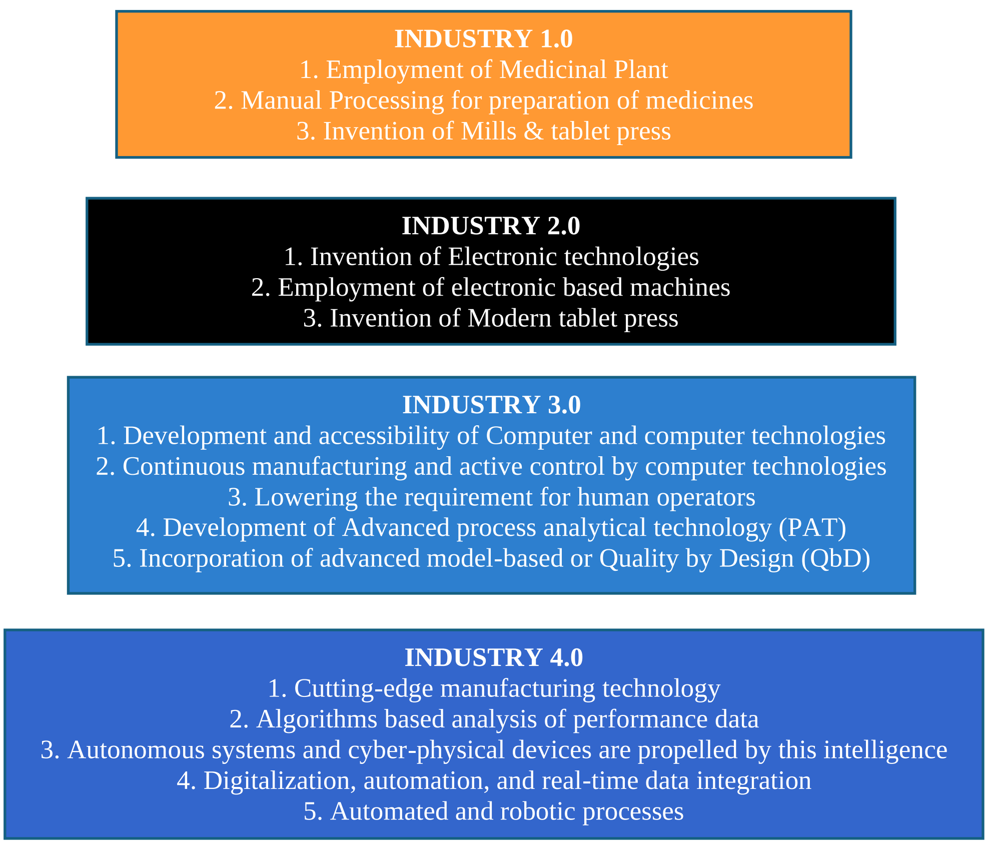

Figure 1: Various Phases of the Pharmaceutical Industry Revolution

These restrictions are especially noticeable in emergencies, such as hospital evacuations, where the effective and flexible distribution of necessary medications can have a direct impact on patient satisfaction. As a result, there is a rising need for creative methods, which may reduce the resource allocation to rapid changes and deliver more accurate demand. To add the responsiveness with efficient medical supply with high stakes like hospitals, suppliers and patients during critical conditions.

In this research work, a duo model that helps in integrating GRU neural network with the help of Mixed Integer Linear programming (MILP). The time series with complex data learning management can be used by GRU neural network model (Dey & Salem, 2017) (Mamoudan et al., 2023).

The Mixed Integer Linear programming (MILP) can be used to reduce resource allocation in different condition for such as storage, logistic cost.

Mixed-Integer Linear Programming models are referred to as MILP models. It is a potent mathematical modeling technique applied to optimization, operations research, and decision-making issues. Mixed-Integer: While some of the model's variables can be continuous (real numbers), others are limited to integer values (often binary: 0 or 1).

The use of linear programming involves all the relationships being linear equations or inequalities, including the objective function and constraints. Use real-world data to meet erratic demand while minimizing overall costs (transportation, holding, ordering, shortage) and guaranteeing prompt and adequate delivery of pharmaceutical products from producers to distribution hubs and pharmacies.

Optimization model utilization of GRU-based forecasting of the data as input, which enables dynamic and reduced resource allocation. The MILP model aims to reduce costs, where it ensures improving service levels, and the E-constraints technique is used to address the challenge faced. MILP generate a collection of Pareto methods by treating to aim as a constraint. Grasshopper Optimization Algorithm (GOA) solves complicated problems more efficiently and effectively. The GOA is a metaheuristic methodology inspired by nature. It solves optimization problems by simulating the swarm behavior of grasshoppers in the wild, specifically how they move in both exploratory and exploitative phases to identify food sources.

Many conventional models are assuming need in estimating continuous and predictable model presented in recent research. For example, the system can Fastly allocate resources to the need location, which high in demand, so that preventing shortage of medicine for patients.

Research work addresses two important issues:

1. Fast forecasting demand fluctuation and Accuracy.

(2) with the help of combining GRU-NN for accurate forecasting, with MILP model for optimization for resource allocation.

In adding to cutting expenses and increasing operational effectiveness, this dual integration strategy allows hospitals to successfully handle patient evacuations in times of emergency, which eventually improves healthcare results. The use of e-constraints methods allows in balancing the objective like cost and services.

According to healthcare report of 2022, the per capita of healthcare has continued to increase over five years as shown in figure 2.

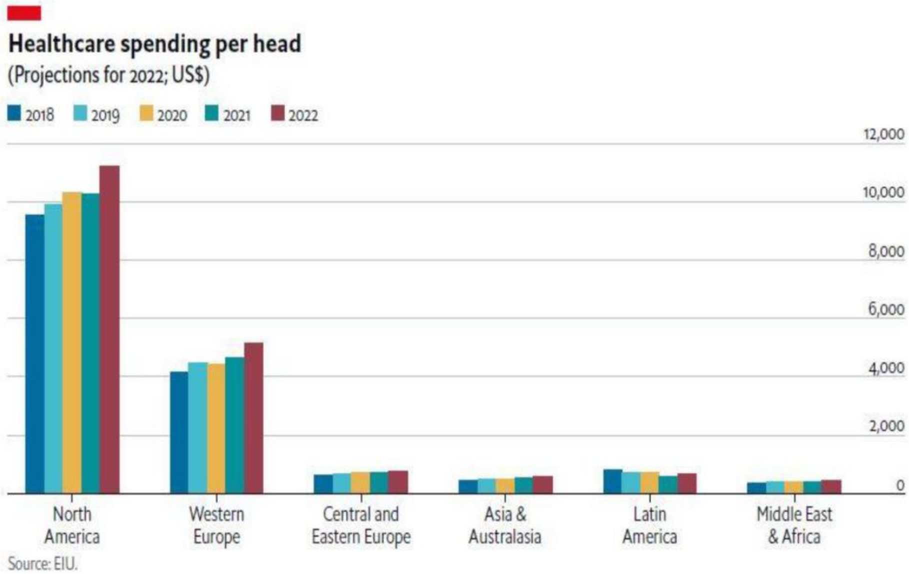

Figure 2: Healthcare spending per head

2 Literature Review

In this research paper, demand forecasting in healthcare, in which investigates the cutting-edge ML and statistical techniques for the improve prediction accuracy, the pharmaceutical supply chain to address issues like reduction in cost, crisis management and innovation in technology.

2.1 Supply Chain for Pharmaceuticals

Most important areas, like the medical supply chain industry, face difficulties in handling the complex variety of industry delivery parties. This field has many use cases, each focusing on distinct areas including technology advancement, flexibility, crisis management and sustainability (Badejo & Ierapetritou, 2024) author address on the multi-objective model, which aims at cost reduction, environmental impacts and an increase in service level equity, which also highlights proactive management in disruption with service level (Rajabi et al., 2024). The author addresses on bi-objective mathematical model for in design of a pharmaceutical supply chain network (Huang et al., 2024). which addresses creating temporary distribution points with inventory backup to increase resilience with the Two Invoice Mechanism (TIM). This model is designed to reduce drug prices in critical conditions (Huang et al., 2024). In this paper, the underfunded retailer’s investigation is conducted for the pharmaceutical supply chain system (Nihlani & Chhabda et al., 2024). The financial at negative interest rates from manufacturers or logistic providers increases the overall profit of medicines (Latonen et al., 2023). In this paper, we introduce a cross-sector collaboration model in critical crises during COVID. This model helps in sharing the resources with stakeholders (Daryanian et al., 2023). In this paper, the author developed a fuzzy robust model for the medical supply chain, in which resilience and sustainability are considered (Ojha & Arora et al., 2024). This model can manage crises, delivery of medicines also reduces the costs (Rekabi et al., 2023). In this paper author addresses on machine learning model for optimization of pharmaceutical supply chain design, using quadratic regression for demand forecasting, which reduces supply chain cost (Sengupta & Deshmukh et al., 2024) (Cuevas-Lopez et al., 2024).

The author is used to address the COVID vaccine supply chain, in this paper, optimizes cost, reduces CO_2 emissions and addresses vaccine storage by considering environmental and economic constraints (Detwal et al., 2023). In this paper, by consider a machine learning model to predict and select the optimal contract for the pharmaceutical supply chain. In this paper, by consider a better decision model for the global pharmaceutical supply chain (Yang, 2023). In this paper author introduces blockchain and deep learning models to optimize supply chain management (Perumalsamy & Kaliyamurthy et al., 2023). In this paper, they have used an ESG-based strategic model for managing the supply chain system (Malleeswaran & Uthayakumar et al., 2022). In this paper, models demonstrate the centralized and decentralized decision-making approaches that lead to an increase in the supply chain system (Ahmad et al., 2022). In this paper mathematical model is designed for optimization of cost to improve the drug and vaccine supply (BenAmor et al., 2022). Pharmaceutical supply chain risk is assessed by the ARAS-BMW approach model. It also reduces mitigation and enhances the supply chain (Romdhani et al., 2022). In this paper, the author introduces a Two-echelon inventory management system for drug deterioration and optimization in replenishment orders (Chen et al., 2024). In this paper, an evolutionary fuzzy approach is used for planning and control of the medicine supply chain and reducing production time (Kochakkashani et al., 2023; Seddigh et al., 2023). Introduce the optimize model for supplying medicine with social media analysis.

2.2 Pharmaceutical and Healthcare Industries Demands

Because of the particulars of the healthcare industry, including fluctuating demands, precise demand forecasting is essential, especially for pharmaceutical supply chains. They are affected by seasonality, patient demands, and market conditions. To tackle the difficulties brought on by uncertainty, a lack of data, and changing market dynamics, academics have actively investigated sophisticated demand prediction techniques in recent years. The most advanced and significant approach involves machine learning and AI to improve the prediction (Angula & Dongo et al., 2024). In this paper, the author introduces the challenges on forecasting the limited availability and relevance of data in an ever-changing market. The author introduces a novel demand forecasting framework using cross-series, with an iterative training approach, which borrows time-series data from various products and applies it with a machine learning model, such as a grouping scheme and learning from non-demanding features (Wiedyaningsih et al., 2024). emphasis on exponential smoothing methods, which includes SES, DES, and TES are a model with highly accurate for forecasting the supply chain data. It also facility of Mean Absolute Percent Error (MAPE) values below 10 percentage. This paper proposes the SES model for data stability, pattern consistency (Fourkiotis & Tsadiras et al., 2024). In this paper author introduces ARIMA, LSTM and XGBoost models with machine learning models for enhancing the pharmaceutical demand with prediction. XGBoost and LSTM neural networks are used to analysis larger sales records of the pharmaceutical supply chain. With several tests, XGBoost outperform in accuracy with achieving lower MAPE and MSE scores (Bhat et al., 2024). In this paper, the author focuses on optimization of medication access in public healthcare through a machine learning stochastic model. (Bilal et al., 2024; Khlie et al., 2024) in this paper, introduce long short-term memory model to gain attention, due to its ability to capture long-term and temporal patterns in time-series data, which is critical for pharmaceutical supply chain demand forecasting.

2.3 Research Division

By considering the various parameters, the pharmaceutical supply chain for critical crises faces various challenges like fluctuating demand, complex logistics, and the need for resource allocation. Recent advancements in utilization of optimal techniques, machine learning and innovative technologies to enhance efficiency and resilience in the pharmaceutical supply chain.

In this paper, a certain innovation is included:

- Utilization of GRU neural network for drug demand forecasting.
- TCC model is used for two destinations for transfer to two different destinations.
- Increase in the pharmaceutical supply chain.
- Use of the Grasshopper Optimization Algorithm to solve complex problems to reduce computational time and improve efficiency of the supply chain.

3 Methodology

The pharmaceutical supply chain creates challenges with limited resources, regulatory restrictions and need swings. This is paired with a mathematical optimization model; effective drug needs can assist in minimising interruptions and guarantee the timely delivery of necessary medications. The application of a mathematical model optimized in conjunction with a GRU-based forecasting model to enhance the supply chain in pharmaceutical operations. In crucial healthcare sectors, this research work illustrates how to improve decision-making, which results in a better resource management math model for precise demand and optimization strategies for resource allocation. improving decision-making can result in better resource management by using ML for precise demand prediction and Operational inefficiencies or deliberate tampering at the production level. Addressing these anomalies involves a twofold approach: enhancing monitoring mechanisms to detect anomalies promptly and investigating the root causes to implement corrective actions. Furthermore, integrating machine learning systems for ongoing anomaly detection can provide continuous oversight, ensuring that supply chain operations remain resilient against emerging challenges (Bilal et al., 2024).

3.1 Model of Prediction

The data analysis and model implementation will be covered in this section, which explains the properties and organization of the training dataset. Following a discussion of the GRI models architecture, the configuration with the precise setup procedure for the model. The assessment is done with the help of the evaluation section using measures like accuracy, recall, precision, F1-Score and ROU-AUC.

3.1.1 Data Collection

The dataset details regarding the availability and demand for medications in various pharmaceuticals throughout time and in emergency situations are provided. details about a particular day and time are included in the dataset, indicating need. It also contains names of medications for patients require such as "diabetes medicines", "Insulin", and "Antibiotic”.

3.1.2 Gated Recurrent Unit

Gated Recurrent Unit is one of the most effective methods created to address the short-term memory in recurrent neural networks (Mousapour Mamoudan et al., 2023). Internal parts called gates that control information flow are part of a GRU. Which sequential information should be retained and discarded is decided by these gates. By carrying out this procedure, the network moves crucial data through the sequence to produce the intended result. Each cell state acts as a network memory, will is considered a crucial component of the GRU architecture. Important details regarding the accessibility and popularity of medications in different medical facilities through time and in emergencies are provided by this dataset. A sigmoid function is used to ensure that the output falls inside [0, 1] after every column of data comprises information about a specific time and date (on a daily or weekly basis), indicating when the corresponding weights are added together. Over the years, these pounds are adjusted during training so that only the most pertinent information is remembered. After that, the output of the gate is calculated by multiplying it elementwise by the concealed state of the previous step. Enough data from the last phase that reduce and reset in this model. An output between [0, 1] is obtained by multiplying (xt) by the new input and the (ht-1) as prior hidden state by their respective weightage, adding them together, and then passing them through a sigmoid function. A unique output vector is produced by applying various weights to the input with the hidden state, which is the main distinction from the update gate. After that, the reset gate output is subjected to a tanh function after being with multi elementwise by the early hidden state.

Updates to the hidden state are then made using the output vector that is produced. The output of the tanh function (r) is multiplied by and updated gate output. From this stage, the updated gate determines new data which needs to be kept in the hidden state. A new hidden state is produced by multiplying the output of the updated gated value-wise by the last hidden value (u) and adding this result. The final output may be the hidden state.

Equations (1) through (4) depict each of these procedures, with Wz, Wr and W serving as weights of learnable matrices. The symbol for the preceding concealed state is (h t−1). xt is the input vector. σ and tanh, respectively, stand for the sigmoid and tanh functions. The letters bz, br, and b stand for the biases. The architecture of this approach is shown in Figure 3 (Misra et al., 2023).

$$zt = \sigma\ (Wz.\ [\ ht\text{-}1,\ xt] + bz\ ) \qquad (1)$$

$$rt = \sigma\ (Wr.\ [ht\text{-}1,\ xt] + br) \qquad (2)$$

$$ht = \tanh\ (W.\ [rt\ .ht\text{-}1,\ xt] + b) \qquad (3)$$

$$ht = (1\text{-}zt).ht\text{-}1 + zt.\ \sim ht \qquad (4)$$

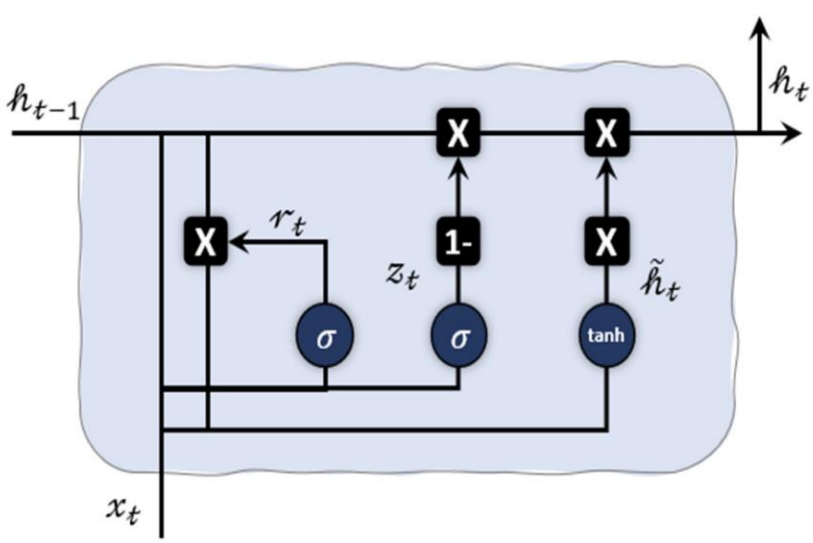

Figure 3: Structure of GRU

3.1.3. GRU Model Configuration

1. Improving Traceability

Temporal data can be processed by GRU to:

- Forecast irregularities in the flow of the supply chain, such as delays or detours.
- Use deviation patterns to model transit behavior and identify possible tampering.
- To avoid shortages or surpluses, estimate demand.

Example: For instance, if a shipment deviates from the anticipated routes or timing, GRU can identify patterns in the GPS records, timestamp, and batch ID and issue alerts.

2. Enhancing Information GRUs can be trained on accuracy using

- Temperature and humidity sensor data streams to identify inaccurate values.
- Use historical shipment data to instantly address discrepancies or fill in any gaps. Multi-source fusion: Creating precise status by combining data from RFID, ERP, and IoT devices.

3. Supply Chain Security

- By identifying typical versus suspicious data patterns, GRU models can be used to identify cyber-physical dangers.
- Identifying irregularities in user behavior or access records in an ERP or blockchain system.
- Example: A GRU model can identify an unusual rise that might indicate tampering if the cargo temperature normally remains between 2 and 8°C.

3.2. Model of Mathematics

The mathematical model is intended to coordinate patient evacuation and medication administration to maximize catastrophe response. numerous interrelated elements are involved, including suppliers, multi-echelon transportation facilities, temporary medical centers (TCCs), receiving hospitals, and evacuation hospitals. The approach aims to minimize overall expenses, decrease interruption risks and patience disconnect, and optimize the network's durability and adaptability. patient evacuation, supply chain management, quotable resources distribution, and changing circumstances.

- The first objective is to minimize the cost with TCC model.
- The second objective is to reduce the risk related to TCC interruption in transportation.
- The third objective is used for network resilience by maximizing TCC.

The model includes several limitations to guarantee a practical and realistic solution to maintain control over patient flow and supply amount; and these include capacity limitations for facilities and transportation vehicles. Figure 4 for a better illustration of the network structure.

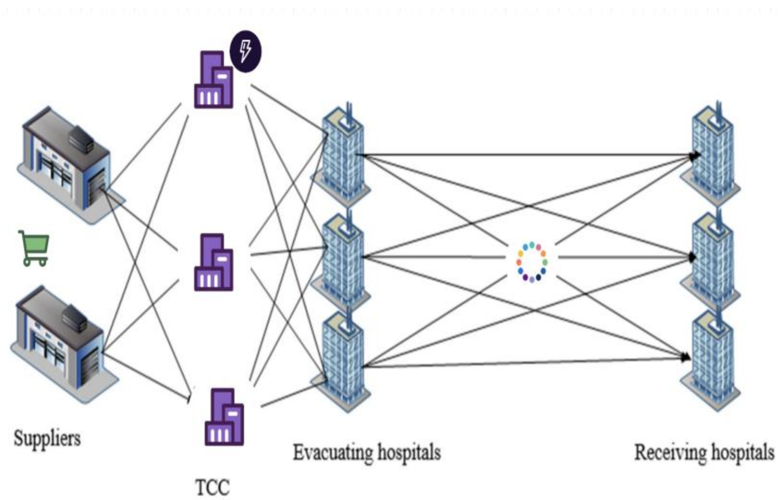

Figure 4: Configuration of the Supply Chain

Temporary care facility buildings might expedite evacuation; however, these establishments may have disruptions and close during catastrophes.

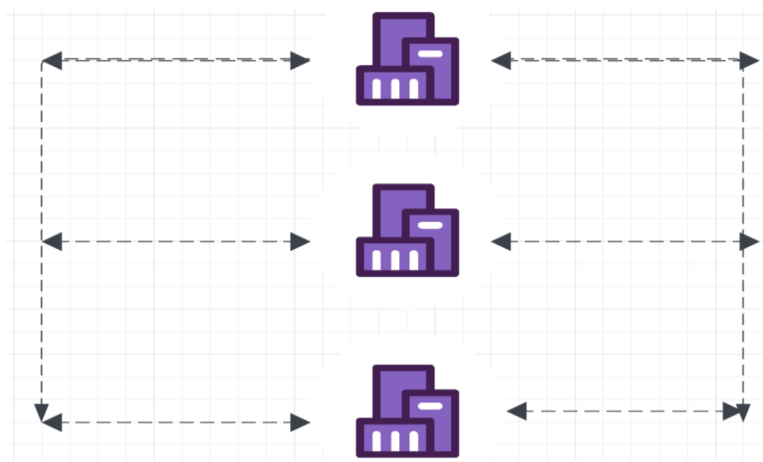

Figure 5: Parallel Setup of TCC

By reducing the interruption risk will increase the supply chain reliability and reduce likelihood of disruptions. Figure 5 shows the TCC model as a parallel system model.

4 Method of Solution

The model like ε-Constraint is widely used for resolving formulations on multi-objective optimization problems by transforming them into single problems. where several competing goals, including data accuracy, security, and traceability, must be balanced. This is done by selecting a primary optimization objective and treating the remaining objective as constraints, each of which is affected by a parameter ε. By carefully adjusting these values, the approach explores various problem scenarios and finds solutions that compromise between opposing objectives. The capacity of this approach to yield Pareto-optimal solutions, outcomes in which no target can be enhanced without making another worse, is one of its main advantages. In this case, the constraint model is:

- f(x) = Data_Accuracy(x) = Maximize

• Subject to $f_3(x)$ = Security_Level(x) $\geq \varepsilon_2$, $x \in X$, and $f_3(x)$ = Traceability(x) $\geq \varepsilon_1$

A strong and transparent pharmaceutical supply chain is made possible by this framework, which enables decision-makers to determine the ideal ratio of security, traceability, and data correctness.

4.1. Algorithm for Grasshopper Optimization

The GOA is a metaheuristic algorithm in which is motivated by nature, emulates the swarming. When grasshoppers are dispersed, they go through a solitary phase; when they are crowded, they go through a swarming phase. By striking a balance between which entails looking for new regions in the solution space and explore entails homing in on existing regions to get the optimum solution GOA replicates these characteristics for optimization problem.

An optimization technique inspired by nature, the Grasshopper Optimization Algorithm (GOA) imitates the swarming and jumping habits of grasshoppers. Grasshopper Optimization Algorithm (GOA) can be used to maximize data accuracy, ensure security, and traceability in the pharmaceutical supply chain. It assists in choosing the best security features, like where to put sensors, RFID readers, and cameras, to guarantee thorough supply chain monitoring. Grasshopper Optimization Algorithm (GOA) can also improve the identification of anomalies and unwanted access, fortifying security measures.

By simplifying the routing of pharmaceutical products, Grasshopper Optimization Algorithm (GOA) can increase the traceability of the supply chain system and provide efficient and live tracking from manufacture to end user. Inventory trace can be improved by optimizing inventory management systems for real-time stock level monitoring at many nodes. Additionally, the Grasshopper Optimization Algorithm (GOA) can be used to optimize smart contracts and blockchain systems, ensuring accurate and secure event tracking across the supply chain.

By spotting discrepancies in sensor data, transaction logs, and shipment records, the Grasshopper Optimization Algorithm (GOA) can help with anomaly detection in terms of data accuracy. By identifying inconsistencies like erroneous batch numbers or expiration dates, it guarantees the accuracy of data. To ensure reliable and consistent datasets for decision-making, the algorithm also aids in optimizing the integration of data from various sources.

The Grasshopper Optimization Algorithm can be used to achieve optimization goals such as reducing supply chain expenses while increasing data accuracy, security, and traceability. Improve pharmaceutical supply chain operations while preserving data integrity and regulatory compliance by modifying factors like warehouse locations, security protocols, encryption types, and mistake tolerance levels.

The pseudocode of the algorithm is shown below:

```
# Initialize parameters

Initialize population size N

Initialize the number of iterations max_iter

Initialize search space boundaries

Initialize grasshopper positions randomly within the search space

# Main GOA loop

for iteration = 1 to max_iter:
```

```
# Evaluate the fitness of all grasshoppers
for i = 1 to N:
fitness[i] = evaluate_fitness(grasshopper[i])
# Find the best grasshopper (Leader)
leader_index = index_of_best(fitness)
leader_position = grasshopper[leader_index]
# Update the position of each grasshopper
for i = 1 to N:
if i != leader_index:
# Calculate distance between grasshopper and leader
distance = calculate_distance(grasshopper[i], leader_position)
# Random jumping behavior: Swarm interaction
jump_factor = random_factor () # Random value to simulate natural jumping
# Update position of grasshopper
grasshopper[i] = grasshopper[i] + (leader_position - grasshopper[i]) * jump_factor / distance
# Ensure the position is within the boundaries
grasshopper[i] = clamp_position(grasshopper[i], search_space_boundaries)
# Optional: Apply local search or exploration/exploitation mechanisms
# Optionally print or log progress (best fitness, current position, etc.)
Print ("Iteration: ", iteration, "Best Fitness: ", fitness[leader_index])
# Output the best solution found
best_solution = leader_position
```

5 Results

The result part delivers a detailed analysis and interpretation of the results in the model implementation. We are summarizing the data and looking at patterns in the demand for pharmaceutical supply chain in various geographic locations and emergency scenarios. The GRU model's forecasting ability is then assessed in the prediction results section using an assessment method to determine how effectively it forecasts drug demand. This model is used to convey the expected drug demand over various periods, and charts are used to depict the analysis and assist supply chain management in making better decisions.

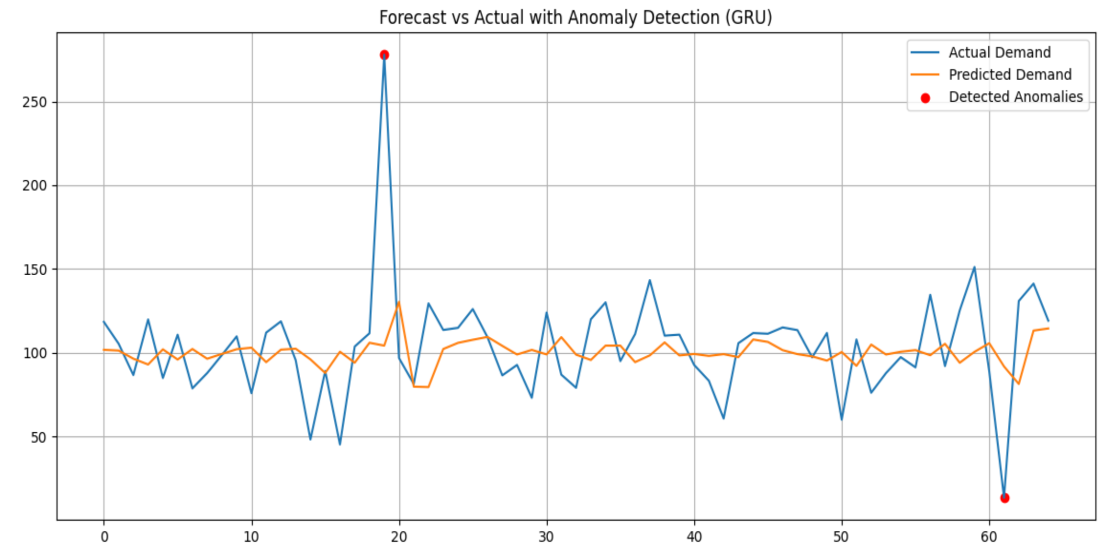

Figure 6: Forecast vs Actual Dataset with Anomaly Detection using GRU

Figure 6 shows a comparison between the actual and anticipated demand using a forecasting model based on the GRU algorithm for the pharmaceutical supply chain dataset. The significant difference between the model predictions and actual values is shown in detected anomalies (red dots), which could be a sign of supply chain interruptions or unforeseen market trends. These models output effectiveness in both predictive and early anomaly detection for preventative decision making.

5.1 Performance of Anomaly Detection and Its Consequences for Pharmaceutical Supply Chain Issues

The pharmaceutical supply chain with highly regulated and sensitive data, even small irregularities can jeopardize product safety, quality, and regulatory compliance. In this field, there are three key challenges:

Security: The possibility of illegal access to inventory systems, fake medications, and online attacks.

Traceability: The need that suppliers, manufacturers, distributors, and pharmacies to have complete visibility and provenance monitoring.

Data Accuracy: Preventing stockouts, overproduction, or non-compliance requires accurate demand, inventory, and shipment data.

Time-series demand data was subjected to a GRU-based model to anomaly identification in this setting. Standard classification measures were used to assessment, as indicated in Table 1.

Table 1: Shows the Dataset Precision, Recall, and F1-score

Class	Label	Precision	Recall	F1-Score	Support
Anomaly	0	0.25	1.00	0.42	16
Normal	1	1.00	0.04	0.08	49
Accuracy	-	-	-	0.28	65
Macro Avg	-	0.63	0.52	0.24	65
Weighted Avg	-	0.82	0.28	0.16	65

Interpretation in the Pharmaceutical Supply Chain Context

The model's high recall (1.00) for anomalies suggests that it was successful in identifying every instance in which behavior deviated from expectations. This could be related to unanticipated demand increases or decreases, illegal database access, or irregular inventory updates in the real world—problems that have a direct impact on security and traceability.

Nonetheless, a substantial false positive rate, in which typical transactions were incorrectly categorized as abnormal, as indicated by the low precision (0.25) for anomalies. This can undermine attempts to maintain operating efficiency by overloading monitoring systems and causing "alert fatigue".

Class imbalance, a prevalent feature in pharmaceutical supply chains where anomalies are uncommon but crucial, is reflected in the low recall (0.04) for the normal class and the overall accuracy of 28%. This indicates that to improve, data accuracy and reliability with balancing strategies or custom threshold adjustments are desperately needed.

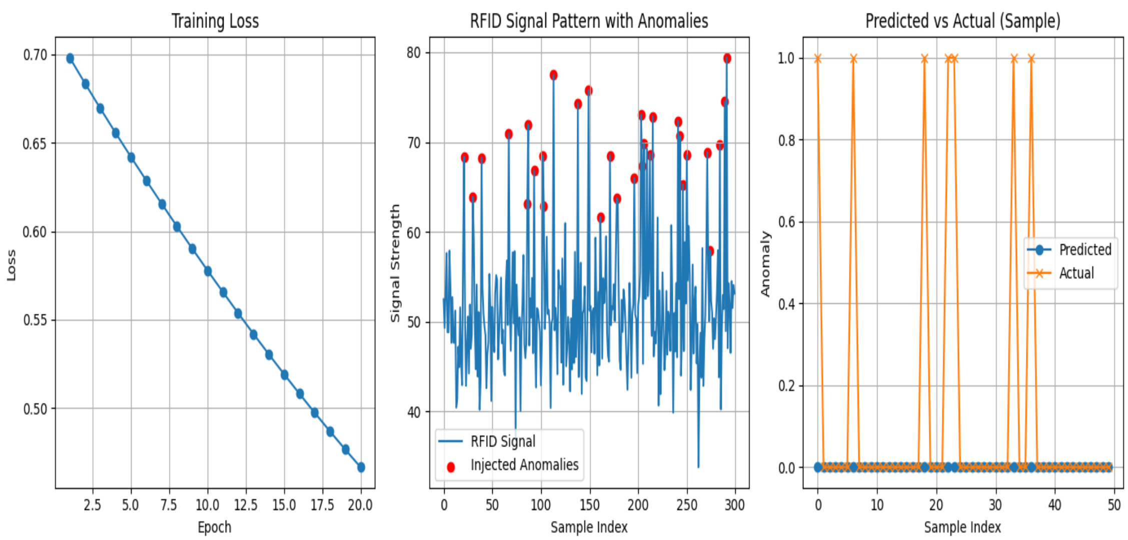

Figure 7: Predicted vs Actual Dataset with Anomaly Detection Test Accuracy (with anomalies): 88.14%

This figure 7 presents an anomaly detection in the PSC using cutting-edge predictive modeling and optimization techniques. The first subplot (left) shows a decreasing training loss, illustrating the effective learning of a GRU neural network over 20 epochs. This neural network makes it possible to estimate medicine demand accurately, which enables dynamic resource allocation a crucial function in emergency situations. The effectiveness of the GRU is essential for proactive decision-making to ensure medicine availability at critical locations.

The primary subplot shows RFID signal strength data, with red dots indicating introduced irregularities. Delays, sabotage, or environmental violations related to transit could be the cause of these anomalies. The data is analyzed using a combination of Mixed-Integer Linear Programming (MILP) and GRU-based detection algorithms. Supply chain routing and allocation optimization are made easier by the MILP. This integrated approach considers a split supply destination, which includes both receiving hospitals and temporary care facilities (TCCs), to guarantee continued medication flow even under strain. By identifying and reacting to anomalies, the technology increases the dependability of patient care and prevents supply disruption.

The last subplot shows excellent identifying anomalies accuracy by contrasting the anticipated anomalies by the GRU model with actual occurrences. This demonstrates how well the GRU-MILP structure works together to preserve supply chain integrity. Security, traceability, and resource optimization are guaranteed by the model's capacity to predict demand while keeping an eye out for logistical irregularities. Such a data-driven strategy is ideal for contemporary, robust pharmaceutical logistics systems since it not only avoids drug shortages but also improves responsiveness.

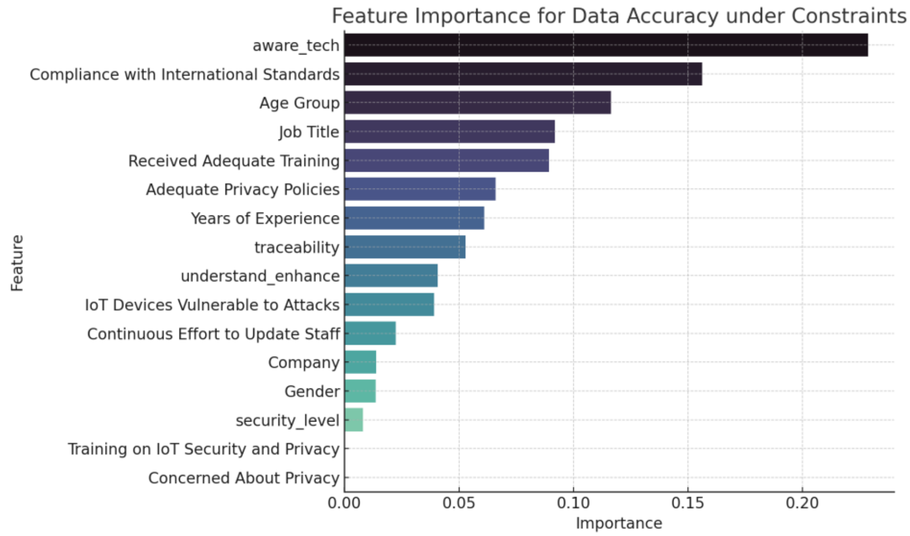

Figure 8: Under the Constraints You Selected (Traceability ≥ 3, Security Level ≥ 3), the Graph Displays the Feature Importance for Predicting Data Accuracy

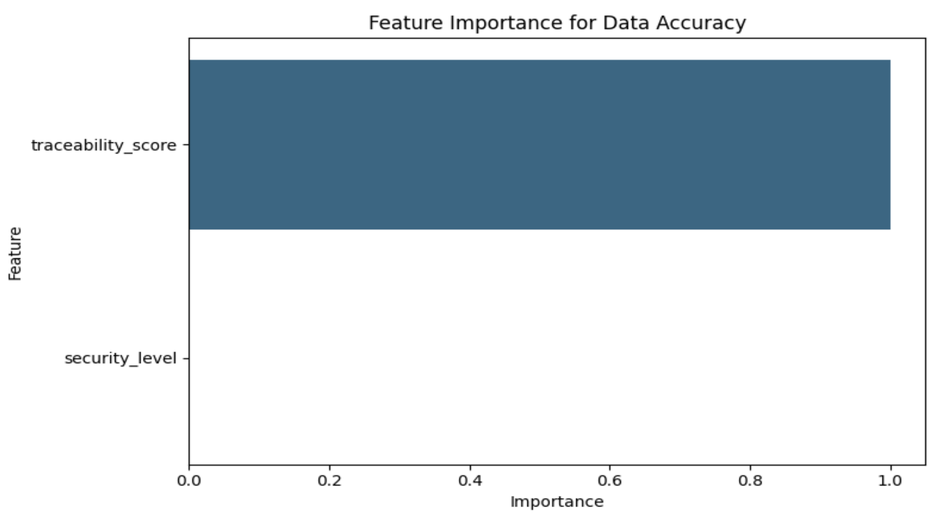

Figure 9: Illustrate the Model's Capacity to Spot Irregularities in the Data Stream, its Performance is Assessed using Accuracy Measures and Displayed Visually

Figures 8 and 9 show that the current study employs a hybrid approach that blends machine learning with optimization to increase the security with traceability of pharmaceutical distribution networks using IoT data. The core methodology consists of two steps: first, anomaly detection using a Gated Recurrent Unit (GRU) network trained on preprocessed IoT sensor data, and second, system parameter optimization using a Grasshopper Optimization Algorithm (GOA) to optimize data accuracy while satisfying security and traceability constraints. The GRU model was selected due to its capacity to handle sequential data and is trained using normalized and encoded attributes extracted from a dataset of IoT security and privacy survey responses.

6 Conclusion

This research highlights critical challenges in the pharmaceutical, which concentrate on enhanced security, traceability, data integrity. Proposed anomaly detection framework offers a proactive approach to identifying vulnerabilities. Future work will focus on applying these methodologies to real-world datasets and exploring advanced machine learning techniques for predictive analytics.

This paper presents a detailed summary of the analysis performed on the supply chain dataset. The dataset consists of 1000 records, and metrics such as total security incidents, average traceability scores, and total data integrity issues are analyzed for each supply chain stage. Effective administration to guaranteeing the availability of necessary medications in the complicated and ever-changing healthcare environment of today. By combining a mathematical optimization methodology with an automated learning-based demand-forecasting model. To optimize the related supply chain and allocation of resources efficiently, this method is combined with a mathematical optimization model based on MILP. The GRU model produced extremely precise demand forecasts, which were crucial inputs to optimize the framework and enable the system to enhance storage and transportation costs. Future implementation with real-time data resource with blockchain technology, with the help of the internet of things, a sensor-based tracking system to track the supply chain in real time.

Finally, the scope of optimization of the model, which include more complex data in real time regulatory changes and fluctuating in delivery cost, may make the system even more adaptable and scalable for supply chain system.

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