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Original Article

Optimized CNN-LSTM Tuple Aggregation Framework with Reinforcement Learning for Real-Time Dairy Production Enhancement

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Abstract - *The present-day dairy industry is dealing with mounting pressure for product quality, cost-effectiveness, and the volatility of supply chain performance. Solving these problems requires intelligent systems to process spatial and temporal information related to real-time working dairy farms. To deal with both spatial and temporal diffusions, in this paper, we introduce a more efficient aggregated framework of splice point signal and propose an Optimized Deep Learning-powered Tuple Aggregation framework combining CNN and LSTM for complete spatiotemporal feature extraction, as well as an RL-based anomaly detection algorithm to detect anomalies in manufacturing processes. The frame can model data tuples of dairy machines, environmental sensors, and quality control checkpoints to predict milk quality, maximise machine allocation, and perform predictive maintenance. By implementing such an integrated system, productivity is improved, wastage is reduced, and the operation of the supply chain is optimized. The experimental results based on monitoring dairy production data in real-time have proven the effectiveness of this model in accuracy, response time, and efficiency as opposed to classical machine learning methods. This study paves the way for completely automated intelligent management of dairy plants for eco-friendly, high-level products.*

Keywords - *Dairy production optimization, Tuple aggregation, CNN-LSTM, Reinforcement learning, Anomaly detection, Spatiotemporal analysis, Predictive maintenance, Supply chain management, Milk quality prediction, Industry 4.0.*

1. Introduction

The global dairy industry is witnessing a tremendous technological revolution driven by the consumer requirement for high quality, minimal wastage of available resources and efficient production practices [1]. Today, many dairy facilities are still manually controlled, using fixed-in-place control systems and reactionary quality assurance systems that are no longer capable of dealing with today's production environments [2]. Besides such traditional tasks, in-line monitoring, anomaly detection, and predictive analytics are in demand more and more to optimize machinery, influence the contemplated equipment , and work continuously for supply chain logistics [3, 4].

Recent developments in deep learning have shown promise in processing large-scale, heterogeneous data from production sites [5, 6]. In this regard, Convolutional Neural Networks CNNs are suitable for extracting spatial features from sensory data. On the other hand, Long Short-Term Memory LSTM networks have better performance in modeling temporal dependencies [7]. That said, these methods are sound in many respects. However, they also tend to be static decision models, weak at real-time anomaly detection and operational control, and these issues can be overcome by some Reinforcement Learning (RL) techniques [8].

To solve the above limitations, Optimized CNN-LSTM Tuple Aggregation with reinforcement learning-based anomaly detection to transform the real-time operation of dairy plants is introduced in this research [9]. This proposed system can conduct comprehensive spatiotemporal analysis by aggregating tuple-based data flows from multiple subsystems such as temperature sensors, equipment fault diagnostics, and quality control outputs, identifying production anomalies, and predicting equipment breakdowns in advance [2].

Despite advances in deep learning for industrial analytics, there is a considerable need for further research in developing predictive modeling with real-time control in the dairy industry. CNN-LSTM-based models for pattern recognition and prediction are successful; however, they passively identify events without any possibility of adaptation or real-time optimization from anomalies encountered. This last limitation is particularly challenging when the process is not static, and decisions are needed quickly to avoid equipment failure, wastage, and loss of production quality. Filling this gap with a framework that not only processes spatiotemporal data but also actuates on the environment to achieve desired operational results is the focus of this work.

The key contributions of this work are:

- Developing a robust tuple aggregation mechanism to handle real-time, diverse, high-frequency data.
- Integrating CNN-LSTM for accurate spatiotemporal feature extraction in dairy production processes.
- Implementing reinforcement learning to detect anomalies and suggest corrective actions dynamically.
- Validating the framework on real-world datasets with measurable productivity, milk quality, and supply chain efficiency improvements.

This paper is organized as follows: Section 2 introduces the related works in innovative dairy production and deep learning applications. The system architecture and methodology are presented in Section 3. Section 4 describes experimental configurations and the evaluation of the performance. Results are discussed in Section 5, and a conclusion and future prospects are summarized in Section 6.

2. Related Works

In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have exploded to improve dairy farm management aspects, such as milk yield prediction, animal health surveillance, and process automation. Such methodologies usually draw on vast amounts of data – from milk yield and environmental data to feeding information and genetic traits – to create decision-support systems that help efficiently manage farm resources. This study used Machine Learning and AI to develop Decision Support Systems (DSS) models for dairy farming. With massive data, including milk records, environmental data, and genetic information, the research goal is for milk production prediction and a complete understanding of the key factors affecting milk production to utilise the breeding resource broadly [10]. It further processes the data together with the expert evaluation to analyze how quality figures (indices) and reports real-time information to the operator, which is decisive for effective herd management and feeding costs [11]. Ten various deep learning methods were compared. The study claims that milk production is an autoregressive process, and the environmental factors cannot capture the external effects [12].

The approach presents a method for mastitis detection using deep learning to combine udder temperature and size features. YOLOv7 detects the eye and udder regions, while CenterNet detects the udder key points [13]. The system is based on deep learning models for extracting entities and relationships, which allows direct answering of questions in natural language while giving insights into cow health and management [14]. The study discusses an intelligent dairy product identification algorithm integrating machine vision and AI based on production line statistics. Using the YogDATA datasets, which contain images of yoghurt cups, Mask R-CNN and YOLOv5 are trained and validated [15].

The approach combines Augmented Reality (AR) and deep learning for estrus detection and cow identification. YOLOv5 detects mounting behavior, identifies cows, and achieves high accuracy in mounting detection (mAP = 94.5%), ROI identification (mAP = 95.4%) and cow ID (mAP = 83.2%) [16]. The research establishes a thermal imager and deep learning-based mastitis identification method. The first classification must be performed with image-enhancement algorithms and multi-scale scSE-DenseNet-201 [17]. The proposed model utilizes the combination of CBAM, GhostConv, and segmentation heads to circumvent the detection of cows, obstacles, and road targets. It achieves excellent precision, recall and mAP on experimental data, allowing it to be implemented on embedded devices [18].

A new model, namely Res-DenseYOLO, for detecting dairy cow behaviors, including drinking, feeding, lying, and standing, is proposed in this study. Specifically, the model consists of dense modules, a CoordAtt attention pathway, and multi-scale detection heads to enhance feature representation and accurate detection of small targets [19]. The Bilateral filter refines the image details, and the MobileNetV3 architecture and multi-scale feature pyramid network optimize the target detection.

This system allows automatic mastitis recognition [20]. The model leveraged supervised machine learning to forecast milk yield, fat, and protein content is given weather and feed data-high accuracy, except for the model for all cows with similar heat tolerance between both cows. Conventional dairy farms are proposed to use an AI system to reduce heat stress and malt quality [21].

The study reports establishing a computer vision system based on a deep learning approach to identify individual cows, recognize their location, and track their trajectories. Precision-recall scores are moderate for the YOLO neural network trained on cow coat patterns [22]. The approach adopts R2Faster R-CNN, a horizontal-oriented object detection framework, for detecting cow teats in rotary milking systems. With high AP and low orientation error, the model facilitates accurate teat cup attach points in automatic milking devices [23]. The model develops a deep convolutional neural network trained on MIR spectra and obtains high accuracy, sensitivity, and specificity. Synthetic data augmentation improves model performance, allowing for early bTB detection in dairy herds [24].

This paper proposes a new combination of CNN-LSTM and Reinforcement Learning (RL) for real-time dairy production optimization, which previous studies have not considered. In contrast to previous works that consider spatial modelling (e.g., using the topology information) or temporal modeling (e.g., in attribute propagation) only, our framework supports pervasive spatiotemporal analysis and adaptive control. The system can detect anomalies using tuple-based data aggregation and RL-inspired decision-making, making it more advanced than static or passive modes.

3. Proposed Methodology

This uncertainty inspired the development of an Optimized Deep Learning-Powered Tuple Aggregation Framework to classify and track real-time environmental data streams across many disparate sources in a dairy production setting. The framework is initiated with a dataset of tuple data values produced from several process stages, including records of machine performance, environmental sensors, and quality criteria checks. These tuples are structured and unstructured data associated with spatial and/or temporal attributes and are collected in a unified data pipeline, into which a preprocessing, normalization, and synchronization process may be applied. We first apply the CNN component on the sensor data to learn discriminative spatial feature maps, which can capture localized activity patterns such as temperature change, pressure variation, and mechanical behaviour across different processing units. After spatial analysis, the LSTM method uses the network to capture the time dependencies and sequential tendency, which can accurately predict the milk quality parameters and the machinery health in the spatial-temporal dimension. In order to improve the responsiveness of the system further, an RL-based anomaly detection module is also incorporated, which continuously observes the processed outputs to identify operational anomalies and performance disruptions. RL agent learns to infer the system state and propose corrective actions, e.g., changing machine parameters, creating maintenance alerts, or redirecting jobs to reduce the disruption.

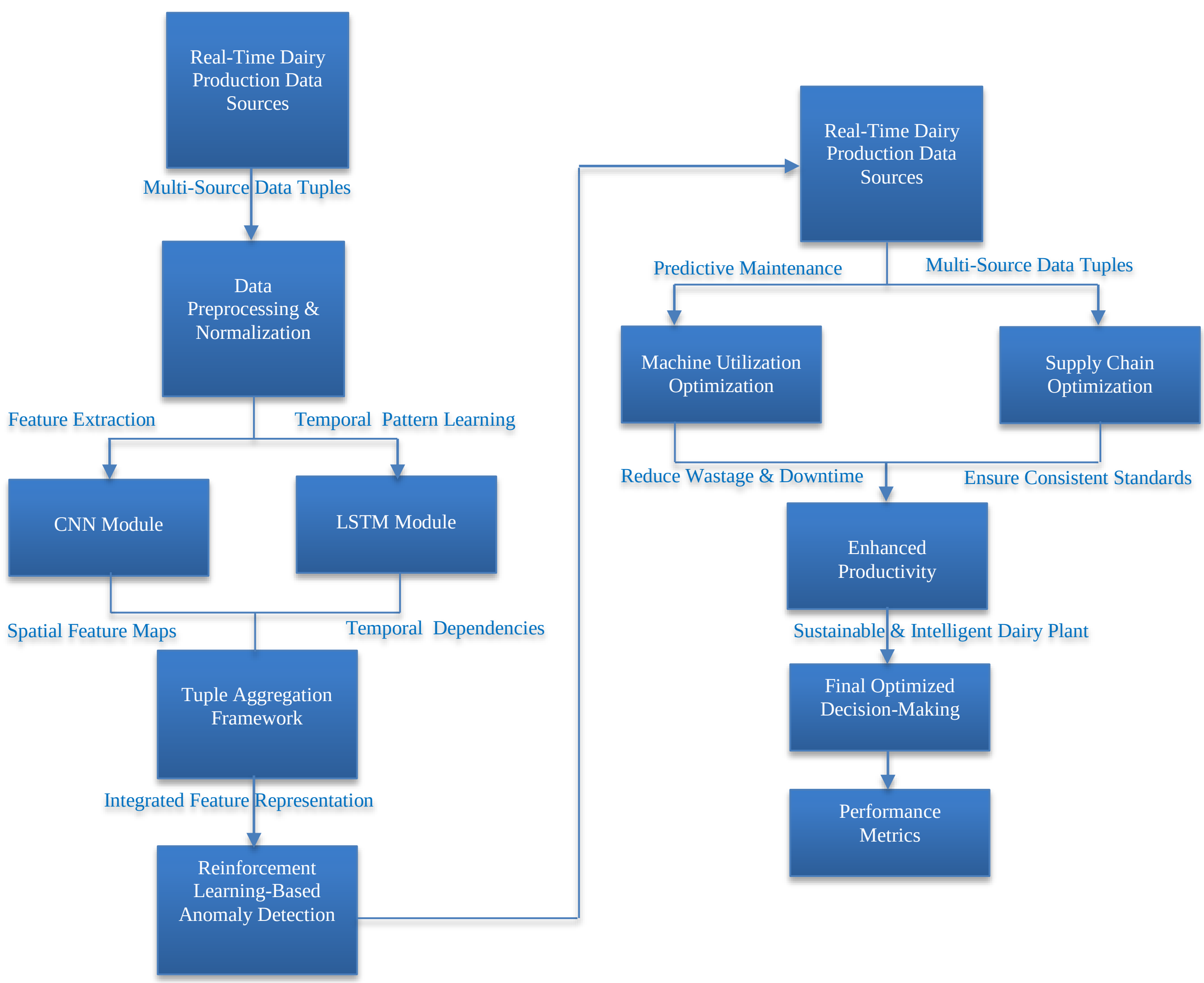

Fig. 1 Optimized CNN-LSTM tuple aggregation framework with reinforcement learning

Figure 1 illustrates the schematic of the proposed framework for real-time improvement of dairy production. Information from multiple sources is first fed to CNN and LSTM modules to achieve spatial and temporal feature extraction, and then tuples are aggregated. Reinforcement learning-powered anomaly detection machines are used in production to predict milk quality, machine utilization, and preventive maintenance. The model supports sustainable, efficient and quality-focused dairy plant management. AI-enabled end-to-end platforms not only predict issues but take corrective action adaptively in real-time to ever-changing production conditions, achieving best-in-class machine uptime, lesser wastages, quality milk and optimized supply chain.

Through this hybrid deep learning approach, the framework enables intelligent decision-making and predictive maintenance, significantly advancing the automation and sustainability of modern dairy production plants.

Step 1: Data Acquisition and Tuple Formation: Data is continuously generated from various subsystems in a modern dairy production environment. These data sources provide heterogeneous information, which must be collected and organized efficiently to support downstream deep-learning tasks. To handle this, defined tuples encapsulate multi-dimensional data attributes, including spatial, temporal, and contextual information.

3.1. Data Acquisition

Real-time data is sourced from the following key components: Machine Performance Metrics**:** Let the machine parameters at time t be represented as:

$$M_t = \{S_t, P_t, T_t\} \tag{1}$$

Where: S_t= Motor speed (RPM) at time t, P_t= Pressure (Pa) at time t, T_t= Machine temperature (°C) at time t.

3.1.1. Environmental Sensor Readings

Environmental conditions influencing production are given by:

$$E_t = \{H_t, AT_t\} \tag{2}$$

Where: H_t=Humidity (%) at time t, AT_t= Ambient temperature (°C) at time t.

3.1.2. Quality Control Data

Milk quality parameters measured during production are:

$$Q_t = \{F_t, PR_t, PH_t\} \tag{3}$$

Where: F_t= Fat content (%) at time t, PR_t= Protein level (%) at time t, PH_t= pH level at time t.

3.1.3. Supply Chain and Logistics Data

To track product movement and storage status:

$$L_t = \{SS_t, DS_t\} \tag{4}$$

Where: SS_t= Storage status (capacity utilization %) at time t, DS_t= Delivery schedule adherence (minutes delayed or early) at time t.

3.2. Tuple Formation

To integrate these heterogeneous data sources into a unified processing framework, define a tuple TUP_t at time t as:

$$TUP_t = (M_t, E_t, Q_t, L_t, t) \tag{5}$$

Explicitly,

$$TUP_t = (\{S_t, P_t, T_t\}, \{H_t, AT_t\}, \{F_t, PR_t, PH_t\}, \{SS_t, DS_t\}, t) \tag{6}$$

Where: M_t, E_t, Q_t, L_t are the data from the respective subsystems, t is the timestamp for sunchronization across all data sources.

3.3. Spatial, Temporal, and Contextual Attributes

For advanced processing, each tuple is enriched with:

- Spatial Attributes: Indicating the physical location or section of the plant where the data originated (e.g., pasteurization unit, cooling system, storage area).
- Temporal Attributes: Timestamps t to maintain time-series integrity, enabling sequence learning via LSTM networks.
- Contextual Attributes: Metadata such as machine IDs, batch numbers, or operator IDs for traceability and deeper analysis.

3.4. Continuous Data Stream Representation

For real-time analysis, tuples form a continuous sequence:

$$D = \{TUP_1, TUP_2, TUP_3, \dots, TUP_n\} \tag{7}$$

Where n represents the total number of data points collected for a measurement period. By formatting production data as tuples, the model is compatible with the CNN-LSTM architecture and can accurately extract spatiotemporal patterns, which is crucial for the downstream reinforcement learning-based anomaly detection module.

Step 2: Data Preprocessing and Aggregation

After tuples are formed, the data must be preprocessed to be clean, synchronized, and well-aggregated for deep learning.

3.4.1. Data Cleaning

Raw data may contain Noise (N_t) and Missing Values (MV_t). The cleaned tuple $Tuple'_t$ is obtained as:

$$Tuple'_t = Tuple_t - (N_t + MV_t) \tag{8}$$

$Tuple_t$=Original tuple at time t, N_t= Noise in the data (e.g., sensor errors, fluctuations), MV_t= Missing values (handled via interpolation or imputation).

3.4.2. Time Synchronization

Each data source has different timestamps $t_1, t_2, \ldots, t_n$. To ensure consistency, all data is synchronized to a standard timeline t_{sync}:

$$t_{sync} = \frac{1}{n}\sum_{i=1}^{n} t_i \tag{9}$$

Where n is the number of data sources, this ensures all data points align correctly for temporal analysis.

3.4.3. Tuple Aggregation

The cleaned and synchronized tuples are aggregated into a unified dataset D for deep learning:

$$D = \bigcup_{t=1}^{T} Tuple'_t \tag{10}$$

Where: D = Final dataset for CNN-LSTM input, T = Total number of time steps. This aggregated dataset is now structured and ready for deep learning models to extract patterns and make predictions.

Step 3: Spatial Feature Extraction using CNN

After preprocessing, the clean and aggregated data D is passed to a CNN to extract spatial features**.**

3.4.4. Input to CNN

Let the input data at time t be:

$$X_t = Tuple'_t \tag{11}$$

This input X_t contains all the relevant parameters (machine data, sensor data, quality control data, etc.).

3.4.5. Convolution Operation

The CNN applies filters (kernels) to detect important spatial patterns:

$$F_t = X_t * K \tag{12}$$

Where F_t= Feature map at time t, X_t= Input tuple data, K= Convolution filter (kernel), $*$= Convolution operation. This step captures local dependencies, like detecting specific behaviors such as:

- Sudden temperature changes.
- Pressure spikes.
- Abnormal quality readings.

3.4.6. Activation Function

After convolution, apply an activation function like ReLU (Rectified Linear Unit) to introduce non-linearity:

$$A_t = ReLU(F_t) \tag{13}$$

Where: A_t= Activated feature map at time t, $ReLu(x) = \max(0, x)$.

3.4.7. Pooling Operation

To reduce the size and focus on the most important features:

$$P_t = Pool(A_t) \tag{14}$$

Where: P_t= Pooled feature map.

3.4.8. Spatial Feature Vector

The final output from the CNN after flattening the feature map is:

$$S_t = Flatten(P_t) \tag{15}$$

Where S_t is the spatial feature vector that captures key spatial characteristics at time t.

Step 4: Temporal Feature Extraction using LSTM

After spatial feature extraction using CNN, the spatial feature vector is obtained. S_t at each time step t. These are passed to an LSTM network to learn temporal (time-based) patterns across the data sequence.

3.4.9. Input Sequence to LSTM

The input to LSTM is the sequence of spatial feature vectors over time:

$$\{S_1, S_2, S_3, \ldots, S_T\} \tag{16}$$

Where: S_t= Spatial feature vector at time t, T= Total number of time steps.

LSTM Cell Operations

For each time step t, LSTM computes:

Forget Gate

Determines which past information to forget:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, S_t] + b_f\right) \tag{17}$$

Input Gate

Decides what new information to store:

$$i_t = \sigma(W_i \cdot [h_{t-1}, S_t] + b_i) \quad (18)$$

Cell State Update

Updates the memory of the network:

$$C_t = f_t * C_{t-1} + i_t * \tanh(W_C \cdot [h_{t-1}, S_t] + b_C) \quad (19)$$

Output Gate

Determines the output at time t:

$$o_t = \sigma(W_o \cdot [h_{t-1}, S_t] + b_o) \quad (20)$$

Hidden State

The final temporal feature at time t:

$$h_t = o_t * \tanh(C_t) \quad (21)$$

Where: h_t=LSTM output (temporal feature) at time t, σ= Sigmoid activation function, W_f, W_i, W_C, W_o= Weight matrices, b_f, b_i, b_C, b_o= Bias terms.

Final Temporal Feature

After processing the whole sequence, get a learned temporal representation:

$$H = \{h_1, h_2, h_3, \ldots, h_T\} \quad (21)$$

Step 5: Anomaly Detection using Reinforcement Learning

After extracting spatial features with CNN and temporal patterns with LSTM, an RL agent is deployed to monitor system outputs and detect anomalies in real time by learning optimal strategies.

RL Environment Setup

The dairy production system is modelled as an RL environment, where:

State (S_t)

Current system status at time t (e.g., machine health, milk quality score, operational flow).

Action (a_t)

Decision made at time t (e.g., adjust machine parameters, schedule maintenance, alert operators).

Reward (r_t)

Feedback for the action taken:

$$r_t = \begin{cases} +1, & \text{if the action improves system stability/quality} \\ -1, & \text{if the action leads to further issues or ignores anomalies} \end{cases} \quad (22)$$

Q-Learning

The agent uses Q-values to learn the best actions:

$$Q(S_t, a_t) = Q(S_t, a_t) + \alpha\left(r_t + \gamma \max_a Q(s_{t+1}, a) - Q(S_t, a_t)\right) \quad (23)$$

Where: $Q(S_t, a_t)$= Value of taking action a_t in state s_t, α= Learning rate, γ= Discount factor, r_t= Immediate reward, $\max_a Q(s_{t+1}, a)$= Estimated best future value.

Step 6: Optimization and Decision-Making

In this final stage, the framework integrates outputs from CNN (spatial features), LSTM (temporal patterns), and Reinforcement Learning (RL) (anomaly detection and corrective actions) to make optimized decisions that enhance the entire dairy production process.

Objective Function for Optimization

Here, define an overall optimization goal to maximize productivity while minimizing wastage and maintaining quality.

$$\text{Maximize } J = U - W + Q - C \quad (24)$$

Where: J= Total performance score (objective function), U= Machine utilization efficiency, W= Wastage (to minimize), Q= Milk quality score, C= Operational costs.

Decision Rule

At each time t, the system uses predictions, and anomaly alters to decide on the best action a_t^*:

$$a_t^* = \arg\max_a (Q(s_t, a) + P_t) \quad (25)$$

Where: a_t^*= Optimal action at time t, $Q(s_t, a)$= RL value of action a in state s_t, P_t= Predicted benefit from CNN-LSTM insights.

Dynamic Adjustments

The system dynamically updates machine parameters M_t and supply chain operations L_t:

$$M_t = M_{t-1} + \Delta M \quad (26)$$

$$L_t = L_{t-1} + \Delta L \quad (27)$$

Where ΔM= Adjustments to machine settings, ΔL= Adjustments to logistics (delivery schedules, storage conditions, etc.).

Step 7: Output Generation and Continuous Learning

At this final stage, the framework delivers real-time insights and learns from operational outcomes to improve performance.

Feedback Loop for Continuous Learning

Once actions are taken, their outcomes F_t (Feedback) are collected:

$$F_t = \text{Result}\ (a_t) \tag{28}$$

Where a_t, is the action chosen by the RL agent, and F_t is the observed outcome (positive or negative impact on the system).

4. Results and Discussions

The proposed Optimized CNN-LSTM Tuple Aggregation Framework with RL was evaluated on real-time dairy production data, assessing its performance across key metrics such as milk quality prediction accuracy, machine utilization, anomaly detection rate, wastage reduction, and overall productivity. Comparative analyses were conducted against traditional machine learning models such as Support Vector Machine (SVM), Random Forest (RF), and conventional LSTM-only architectures.

4.1. Milk Quality Prediction Accuracy

The integrated CNN-LSTM model demonstrated superior capabilities in predicting milk quality by effectively capturing spatial (sensor-based) and temporal (time-series) variations. As shown in Table 1, the proposed method achieved an accuracy of 97.2%, outperforming SVM and RF models that failed to capture complex, multi-dimensional relationships within the dataset.

Table 1. Milk quality prediction accuracy (%)

Model	Accuracy (%)
SVM	89.4
Random Forest (RF)	91.2
LSTM	94.8
Proposed CNN-LSTM-RL	97.2

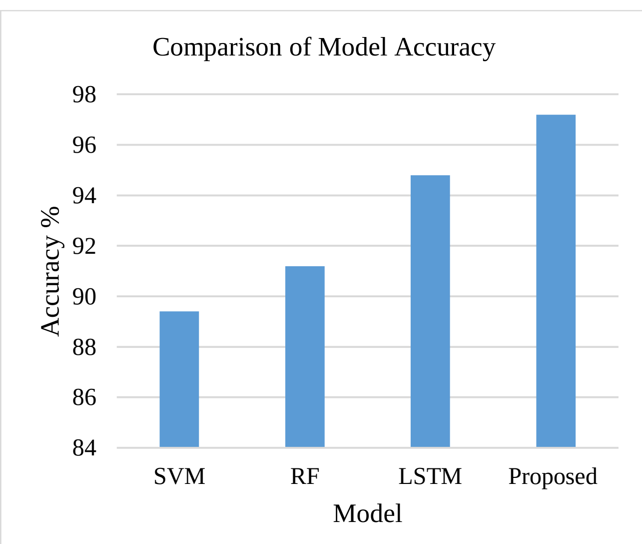

Fig. 2 Comparison of model accuracy for dairy production optimization

Figure 2 visually compares the accuracy of different models for dairy production optimization. The proposed CNN-LSTM-RL model achieves the highest accuracy (97.2%), outperforming SVM (89.4%), Random Forest (91.2%), and LSTM (94.8%). The results highlight the effectiveness of the proposed framework in enhancing prediction accuracy for real-time dairy production systems.

4.2. Machine Utilization and Operational Efficiency

The proposed framework achieved enhanced machine utilisation through anomaly detection and adaptive optimization via reinforcement learning. The system could identify operational inefficiencies and suggest real-time corrective actions, improving utilization rates from 84.5% to 93.1%, as indicated in Table 2. This was significantly better than baseline models that lacked dynamic learning capabilities.

Table 2. Machine utilization comparison

Model	Machine Utilization (%)
Traditional Control	84.5
LSTM-based System	88.0
Proposed Framework	93.1

Figure 3 presents the machine utilization percentage across three different approaches: Traditional Control (84.5%), LSTM-based system (88.0%), and the Proposed Framework (93.1%). The proposed CNN-LSTM-RL framework demonstrates superior machine utilization, emphasizing its efficiency in optimizing dairy production processes.

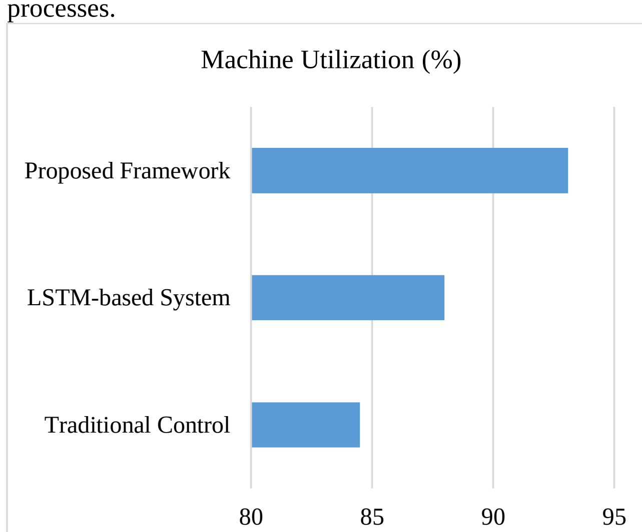

Fig. 3 Comparison of machine utilization in dairy production systems

4.3. Anomaly Detection Performance

The reinforcement learning component of the framework played a pivotal role in identifying and mitigating anomalies. The performance result is presented in Table 3, and we can see that the proposed approach achieved a 95.6% anomaly detection rate over traditional threshold-based and statistical anomaly detection methods.

Table 3. Anomaly detection rate (%)

Method	Detection Rate (%)
Statistical Thresholding	80.2
Isolation Forest	87.5
Proposed RL-based Detection	**95.6**

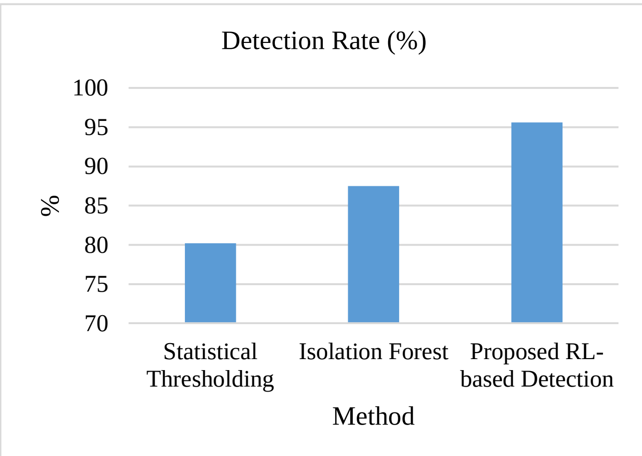

Fig. 4 Comparison of Anomaly Detection Methods in Dairy Production

Figure 4 illustrates the detection rate of three different anomaly detection methods: Statistical Thresholding (80.2%), Isolation Forest (87.5%), and the Proposed RL-based Detection (95.6%). The proposed Reinforcement Learning (RL)-based detection system significantly outperforms traditional methods, ensuring more accurate anomaly identification in dairy production.

4.4. Wastage Reduction

By promptly identifying quality deviations and equipment failures, the system reduced milk wastage by approximately 32% compared to conventional operations, as shown in Table 4.

Table 4. Milk wastage reduction comparison

Method	Wastage (%)
Without Optimization	14.5
LSTM-based Prediction Only	10.1
Proposed Framework	6.8

This bar chart illustrates the impact of different optimization techniques on wastage reduction in dairy production. The "Without Optimization" approach results in the highest wastage (14.5%), followed by the "LSTM-based Prediction Only" method (10.1%). The Proposed Framework significantly reduces wastage to 6.8%, demonstrating its effectiveness in optimizing resource utilization.

The experimental results show the superiority of the CDN-LSTM-RL model over traditional and independent deep learning algorithms in handling the complexities of a real-life dairy production environment. Through the use of tuple-based aggregation, the system is capable of effectively handling various data forms and also delivers actionable knowledge. By reinforcement learning, an optimal framework for the new condition is maintained, which eases other works such as predictive maintenance, anomaly mitigation, etc. The combination of spatial, temporal, and adaptive learning models makes this approach robust for industrial applications. Moreover, the significant improvements in prediction accuracy, machine utilization, and anomaly detection validate the practical applicability of the proposed model.

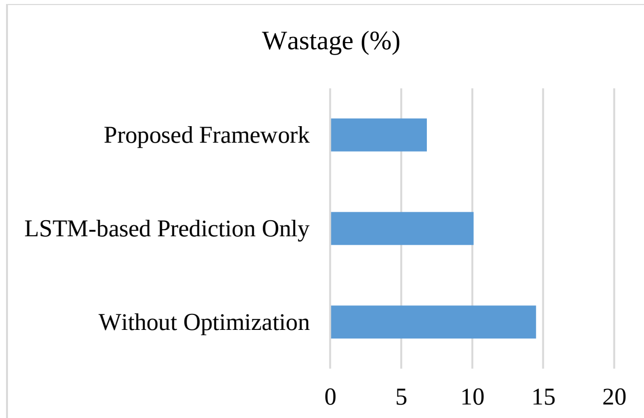

Fig. 5 Impact of Optimization on Dairy Production Wastage

Reduced wastage and enhancement of supply chain logistics further solidify the model's potential for deployment in real-world dairy plants, contributing to sustainable and cost-effective production.

5. Conclusion

This study proposed an Optimized CNN-LSTM Tuple Aggregation Framework integrated with RL to enhance real-time dairy production management. The framework effectively processes multi-source production data, extracting spatial and temporal features to predict milk quality, optimize machine utilization, detect anomalies, and minimize wastage. The proposed system demonstrated superior performance over traditional models through extensive evaluation, achieving higher prediction accuracy, improved operational efficiency, and significantly reduced wastage. The reinforcement learning component enabled continuous monitoring and adaptive decision-making, ensuring proactive maintenance and optimized supply chain operations. The framework offers a robust, intelligent solution for modern dairy plants, supporting sustainable production with minimal losses and maximum productivity. This research paves the way for deploying advanced deep learning-driven automation in the dairy industry, ensuring consistent product quality and operational excellence in real-time environments.

References

[1] S. Ali Naqvi et al., "Mastitis Detection with Recurrent Neural Networks in Farms using Automated Milking Systems," *Computers and Electronics in Agriculture*, vol. 192, pp. 1-10, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[2] M.H. Ghaffari et al., "Deep Convolutional Neural Networks for the Detection of Diarrhea and Respiratory Disease in Preweaning Dairy Calves Using Data from Automated Milk Feeders," *Journal of Dairy Science*, vol. 105, no. 12, pp. 9882-9895, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[3] S. Ali Naqvi et al., "Data Considerations for Developing Deep Learning Models for Dairy Applications: A Simulation Study on Mastitis Detection," *Computers and Electronics in Agriculture*, vol. 196, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] Dariusz Piwczyński et al., "Forecasting the Milk Yield of Cows on Farms Equipped with Automatic Milking System with the Use of Decision Trees," *Animal Science Journal*, vol. 91, no. 1, pp. 1-10, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[5] Rodrigo da Rosa Righi et al., "Towards Combining Data Prediction and Internet of Things to Manage Milk Production on Dairy Cows," *Computers and Electronics in Agriculture*, vol. 169, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[6] I.R. Porter, M. Wieland, and P.S. Basran, "Feasibility of the Use of Deep Learning Classification of Teat-end Condition in Holstein Cattle," *Journal of Dairy Science*, vol. 104, no. 4, pp. 4529-4536, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[7] Jessica Nye, Laura M. Zingaretti, and Miguel Pérez-Enciso, "Estimating Conformational Traits in Dairy Cattle with Deepaps: A Two-Step Deep Learning Automated Phenotyping and Segmentation Approach," *Frontiers in Genetics*, vol. 11, pp. 1-9, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[8] Yanchao Wang et al., "Deep Learning-Based Automatic Dairy Cow Ocular Surface Temperature Detection from Thermal Images," *Computers and Electronics in Agriculture*, vol. 202, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Olli Koskela et al., "Deep Learning Image Recognition of Cow Behavior and An Open Data Set Acquired Near an Automatic Milking Robot," *Agricultural and Food Science*, vol. 31, no. 2, pp. 89-103, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] Mohammad Alwadi et al., "Smart Dairy Farming for Predicting Milk Production Yield Based on Deep Machine Learning," *International Journal of Information Technology*, vol. 16, pp. 4181-4190, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[11] Jae Gu Lee et al., "Utilizing 3D Point Cloud Technology with Deep Learning for Automated Measurement and Analysis of Dairy Cows," *Sensors*, vol. 24, no. 3, pp. 1-21, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Luigi Cesarini et al., "Comparison of Deep Learning Models for Milk Production Forecasting at National Scale," *Computers and Electronics in Agriculture*, vol. 221, pp. 1-21, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Mengyuan Chu et al., "Fusion of Udder Temperature and Size Features for the Automatic Detection of Dairy Cow Mastitis Using Deep Learning," *Computers and Electronics in Agriculture*, vol. 212, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] Junsheng Zhu, René Lacroix, and Kevin M. Wade, "Automated Extraction of Domain Knowledge in the Dairy Industry," *Computers and Electronics in Agriculture*, vol. 214, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Fotios K. Konstantinidis et al., "Automating Dairy Production Lines with the Yoghurt Cups Recognition and Detection Process in the Industry 4.0 Era," *Procedia Computer Science*, vol. 217, pp. 918-927, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Ibrahim Arıkan et al., "Estrus Detection and Dairy Cow Identification with Cascade Deep Learning for Augmented Reality-Ready Livestock Farming," *Sensors*, vol. 23, no. 24, pp. 1-19, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] Mengyuan Chu et al., "Deep Learning-Based Model to Classify Mastitis in Holstein Dairy Cows," *Biosystems Engineering*, vol. 252, pp. 92-104, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[18] Fuyang Tian et al., "An Efficient Multi-Task Convolutional Neural Network for Dairy Farm Object Detection and Segmentation," *Computers and Electronics in Agriculture*, vol. 211, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Rongchuan Yu et al., "Research on Automatic Recognition of Dairy Cow Daily Behaviors Based on Deep Learning," *Animals*, vol. 14, no. 3, pp. 1-19, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] Xudong Zhang et al., "Automatic Recognition of Dairy Cow Mastitis from Thermal Images by a Deep Learning Detector," *Computers and Electronics in Agriculture*, vol. 178, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[21] Sigfredo Fuentes et al., "Artificial Intelligence Applied to a Robotic Dairy Farm to Model Milk Productivity and Quality Based on Cow Data and Daily Environmental Parameters," *Sensors*, vol. 20, no. 10, pp. 1-11, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[22] Patrizia Tassinari et al., "A Computer Vision Approach Based on Deep Learning for the Detection of Dairy Cows in Free Stall Barn," *Computers and Electronics in Agriculture*, vol. 182, pp. 1-38, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[23] Zhiheng Lu et al., "Automatic Teat Detection for Rotary Milking System Based on Deep Learning Algorithms," *Computers and Electronics in Agriculture*, vol. 189, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[24] S.J. Denholm et al., "Predicting Bovine Tuberculosis Status of Dairy Cows from Mid-Infrared Spectral Data of Milk Using Deep Learning," *Journal of Dairy Science*, vol. 103, no. 10, pp. 9355-9367, 2020. [CrossRef] [Google Scholar] [Publisher Link]