

Hybrid CNN–LSTM Framework for Detection of Heavy Metal Contamination in Agricultural Water

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Abstract: Contamination of agricultural water by heavy metals has become a major environmental and public health concern due to rapid industrialization, excessive fertilizer usage, and improper wastewater disposal practices. Continuous use of contaminated irrigation water negatively affects soil fertility, crop productivity, and food safety, leading to severe ecological and human health risks. Traditional laboratory-based water quality assessment methods are often time-consuming, expensive, and unsuitable for real-time monitoring applications. To address these limitations, this paper proposes a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) framework for intelligent detection and prediction of heavy metal contamination in agricultural water systems.

The proposed model integrates the feature extraction capability of CNN with the temporal learning strength of LSTM to analyse multidimensional water quality parameters such as pH, turbidity, electrical conductivity, dissolved oxygen, temperature, and concentrations of heavy metals including lead (Pb), cadmium (Cd), arsenic (As), and mercury (Hg). Sensor-based and historical water quality datasets are utilized for training and validation of the framework. Data pre-processing techniques including normalization, missing value handling, and noise reduction are applied to improve model efficiency and prediction accuracy.

Experimental results demonstrate that the hybrid CNN–LSTM model achieves superior performance compared with conventional machine learning techniques in terms of accuracy, precision, recall, and prediction stability. The proposed system enables early detection of contamination patterns and supports real-time agricultural water quality monitoring for sustainable irrigation management. Furthermore, the framework can be integrated with IoT-enabled smart farming systems for automated environmental assessment and decision support.

The study highlights the potential of advanced deep learning approaches in enhancing sustainable agricultural practices, minimizing health risks, and improving water resource management. The proposed intelligent monitoring framework offers a scalable and efficient solution for future smart irrigation and environmental protection applications.

Keywords: Sustainable Agriculture; Hybrid CNN–LSTM; Water Pollution Detection; Smart Irrigation Systems;; Water Quality Prediction

Introduction

Water quality plays a vital role in sustainable agriculture and food security. In recent decades, rapid industrialization, urbanization, mining operations, and excessive agricultural chemical usage have significantly increased the contamination of irrigation water sources with toxic heavy metals such as lead (Pb), cadmium (Cd), chromium (Cr), arsenic (As), mercury (Hg), and nickel (Ni). These contaminants accumulate in agricultural soils and crops through irrigation practices, affecting crop productivity, soil fertility, and human health through the food chain [1]. Heavy metal contamination in agricultural water has become a major environmental challenge, especially in developing countries where untreated industrial wastewater is frequently used for irrigation purposes [2].

Traditional laboratory-based techniques for detecting heavy metal contamination, including atomic absorption spectroscopy (AAS), inductively coupled plasma mass spectrometry (ICP-MS), and chemical analysis methods, provide accurate measurements but are often costly, time-consuming, and unsuitable for real-time monitoring applications [3]. Moreover, these methods require skilled professionals and sophisticated laboratory infrastructure, limiting their practical implementation in remote agricultural regions. Therefore, there is an increasing demand for intelligent, automated, and cost-effective systems capable of monitoring water quality continuously and accurately.

Recent advancements in artificial intelligence (AI), machine learning (ML), and deep learning (DL) have introduced new possibilities for environmental monitoring and smart agriculture systems. Deep learning models are highly effective in identifying complex nonlinear relationships and hidden patterns from large-scale environmental datasets [4]. Among these approaches, Convolutional Neural Networks (CNNs) are widely used for extracting spatial features and identifying significant patterns from multidimensional sensor data, while Long Short-Term Memory (LSTM) networks are effective for analysing temporal dependencies and sequential variations in time-series datasets [5]. The integration of CNN and LSTM models into a hybrid deep learning framework has demonstrated superior performance in various prediction and classification tasks, including water quality analysis, environmental forecasting, and pollution detection [6].

The proposed Hybrid CNN–LSTM Framework combines the strengths of CNN and LSTM architectures for efficient detection of heavy metal contamination in agricultural water. In this framework, CNN layers are utilized to extract meaningful spatial features from water quality parameters such as pH, dissolved oxygen, turbidity, electrical conductivity, temperature, total dissolved solids, and heavy metal concentrations. Subsequently, LSTM layers process the sequential behaviour and temporal variations of these features to identify contamination trends and predict water quality conditions over time. This hybrid architecture improves detection accuracy, reduces prediction errors, and supports early warning mechanisms for contaminated irrigation systems.

Furthermore, the integration of IoT-based water quality sensors with deep learning frameworks enables real-time monitoring and intelligent decision-making in precision agriculture environments [7]. The implementation of smart water monitoring systems can help farmers, environmental agencies, and policymakers optimize irrigation practices, reduce environmental pollution, and ensure sustainable agricultural productivity. The proposed framework also contributes toward the development of smart farming technologies and sustainable water resource management strategies.

This study focuses on developing a Hybrid CNN–LSTM Framework for the detection of heavy metal contamination in agricultural water using advanced deep learning techniques. The proposed system aims to provide accurate contamination prediction, efficient feature extraction, and real-time monitoring capability for sustainable agricultural water management and environmental protection.

Related work

The detection and prediction of heavy metal contamination in agricultural water have gained significant attention in recent years due to the increasing risks posed to soil fertility, crop productivity, and human health. Conventional laboratory-based techniques for heavy metal analysis are often expensive, time-consuming, and unsuitable for real-time monitoring. Consequently, researchers have increasingly focused on artificial intelligence (AI), machine learning (ML), and deep learning (DL) approaches to develop intelligent and automated water quality assessment systems. Among these approaches, hybrid CNN–LSTM frameworks have emerged as powerful solutions because they combine the spatial feature extraction capability of Convolutional Neural Networks (CNNs) with the temporal sequence learning ability of Long Short-Term Memory (LSTM) networks.

In 2023, Zhang et al. proposed a CNN-based heavy metal ion detection method for improving the efficiency and automation of heavy metal analysis. Their model demonstrated that CNN architectures can effectively extract hidden features from sensing data and significantly improve detection accuracy compared with traditional analytical approaches. The study highlighted the importance of deep learning in rapid heavy metal detection and provided the foundation for integrating advanced hybrid models in environmental monitoring applications.

Similarly, Li et al. (2023) introduced an Attention-Based CNN-LSTM framework for wastewater quality prediction. Their model combined CNN layers for feature extraction with LSTM layers for temporal learning and further incorporated an attention mechanism to improve prediction performance. The proposed CNN-LSTM-Attention (CLATT) model achieved superior accuracy in forecasting wastewater quality parameters and demonstrated the effectiveness of hybrid deep learning architectures in water quality management systems.

Al-Shourbaji and Duraibi (2023) developed IWQP4Net, an efficient CNN model for irrigation water quality prediction. The study focused on intelligent irrigation systems and demonstrated that CNN-based frameworks can accurately predict irrigation water quality using sensor data. Their work emphasized the role of deep learning in smart agriculture and sustainable water resource management.

Hu et al. (2023) proposed a hybrid temporal convolution network for river water quality prediction using time-series analysis. The research addressed the nonlinear and seasonal characteristics of water quality data and achieved improved prediction accuracy over conventional machine learning techniques. Their findings showed that hybrid deep learning models are highly suitable for environmental monitoring applications involving dynamic water quality parameters.

Another important contribution was presented by Özgenç et al. (2023), who applied a hybrid CNN-LSTM model for anomaly detection in water treatment systems. Their framework successfully identified abnormal conditions in water treatment datasets and demonstrated high efficiency in detecting irregular

contamination patterns. This research further validated the applicability of CNN-LSTM architectures in intelligent water monitoring systems.

In the agricultural domain, researchers also explored hyperspectral imaging and CNN techniques for detecting heavy metal stress in crops. A 2023 study published in *Microchemical Journal* utilized hyperspectral imaging (HSI) combined with CNN models to detect copper (Cu) stress levels in apple rootstocks. The CNN model outperformed traditional classification methods and provided rapid, non-destructive detection of heavy metal contamination in agricultural environments.

Obaid et al. (2023) investigated heavy metal contamination in agricultural water, soil, and plants in Afghanistan. Their work highlighted the serious environmental and health risks associated with wastewater irrigation and emphasized the necessity for intelligent monitoring frameworks capable of continuous contamination assessment.

In 2024, Karbasi et al. proposed a hybrid CNN-LSTM model enhanced with Boruta-XGBoost feature selection for forecasting river electrical conductivity, which is a critical indicator of water salinity and contamination. The hybrid model demonstrated excellent prediction performance for multistep forecasting and proved highly effective for complex water quality datasets.

Bounoua et al. (2024) compared ConvLSTM and CNN-LSTM models for forecasting agricultural water stress using remote sensing images. Their study revealed that CNN-LSTM architectures effectively captured spatial and temporal variations in irrigation-related datasets, making them suitable for precision agriculture and environmental monitoring applications.

A significant advancement in intelligent water monitoring was reported in 2024 through a CNN-LSTM-based river water quality monitoring framework developed for the Kaveri River. The proposed model integrated sensor networks with deep learning and achieved an accuracy of 98.40% in water quality evaluation. The study demonstrated that CNN-LSTM models can provide reliable real-time monitoring and decision support for sustainable water management.

Rahul Gandh et al. (2024) proposed attention-driven LSTM and GRU models for precise water quality prediction in smart aquaculture systems. Their research showed that recurrent neural network architectures with attention mechanisms improve prediction accuracy for dynamic aquatic environments and can support sustainable agricultural water monitoring.

Recent studies published in 2025 and 2026 have further explored hybrid CNN-LSTM models in agricultural and environmental applications. Researchers increasingly focus on lightweight and resource-efficient CNN-LSTM architectures for real-time deployment in IoT-enabled environmental monitoring systems. These studies emphasize reduced computational complexity, improved classification accuracy, and better adaptability to large-scale agricultural datasets.

Overall, the literature indicates that hybrid CNN-LSTM frameworks provide superior performance for water quality prediction, anomaly detection, and heavy metal contamination analysis. CNN models effectively extract spatial and spectral features from sensor and imaging data, while LSTM networks capture temporal dependencies in time-series datasets. The integration of attention mechanisms, feature selection algorithms, hyper spectral imaging, and IoT-enabled sensing systems further enhances prediction accuracy and real-time monitoring capabilities. However, challenges such as dataset

availability, model interpretability, computational complexity, and real-time deployment still require further investigation. Therefore, the proposed Hybrid CNN–LSTM Framework for Detection of Heavy Metal Contamination in Agricultural Water aims to address these limitations by developing an intelligent, accurate, and scalable deep learning model for sustainable agricultural water quality monitoring.

Method, Experiments and Results

The proposed Hybrid CNN–LSTM Framework for Detection of Heavy Metal Contamination in Agricultural Water is designed to provide accurate and real-time identification of contamination levels in irrigation water. The methodology combines Convolutional Neural Networks (CNNs) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for temporal sequence learning. The framework integrates sensor-based water quality monitoring with deep learning algorithms to classify and predict heavy metal contamination levels such as lead (Pb), cadmium (Cd), chromium (Cr), arsenic (As), mercury (Hg), and copper (Cu).

Data Collection

The first stage of the methodology involves collecting agricultural water quality data from multiple sources such as:

- IoT-based water quality sensors
- Public environmental datasets
- Laboratory water sample analysis
- Government environmental monitoring agencies

The dataset includes several physicochemical and heavy metal parameters:

- pH
- Electrical Conductivity (EC)
- Dissolved Oxygen (DO)
- Turbidity
- Temperature
- Total Dissolved Solids (TDS)
- Nitrate concentration
- Lead (Pb)
- Cadmium (Cd)
- Chromium (Cr)
- Arsenic (As)
- Mercury (Hg)

Time-series measurements are recorded continuously to capture temporal variations in contamination levels.

Data Preprocessing

Data preprocessing is essential to improve model performance and reduce noise in the dataset. The preprocessing stage includes:

a) Missing Value Handling

Missing sensor readings are replaced using interpolation and mean substitution methods.

b) Noise Removal

Outliers and abnormal values are filtered using statistical normalization techniques such as Z-score normalization and Min-Max scaling.

c) Feature Selection

Important features influencing contamination levels are selected using correlation analysis and feature importance algorithms such as XGBoost and Principal Component Analysis (PCA).

d) Data Segmentation

The dataset is divided into:

- 70% training data
- 15% validation data
- 15% testing data

The data are transformed into sequential time windows suitable for LSTM learning.

Proposed Hybrid CNN–LSTM Architecture

The proposed framework consists of two major deep learning components:

a) CNN Layer for Spatial Feature Extraction

The CNN layer extracts hidden spatial patterns from multidimensional sensor data.

Main CNN operations include:

- Convolution layer
- ReLU activation
- Max-pooling layer
- Feature map generation

The CNN effectively identifies local relationships among water quality parameters and contamination patterns.

b) LSTM Layer for Temporal Analysis

The extracted CNN features are passed into the LSTM network to capture temporal dependencies and sequential variations in water quality measurements.

The LSTM network contains:

- Input gate
- Forget gate
- Output gate
- Memory cell

LSTM is highly effective for analyzing time-series environmental datasets because it retains long-term dependencies and historical contamination trends.

c) Fully Connected Layer

The final dense layer performs contamination classification and prediction.

Output classes include:

- Safe water
- Moderately contaminated water
- Highly contaminated water

The framework can also predict individual heavy metal concentration levels.

Model Training

The hybrid CNN–LSTM model is trained using the Adam optimizer and categorical cross-entropy loss function.

Training Parameters

- Epochs: 100
- Batch size: 32
- Learning rate: 0.001
- Optimizer: Adam

The training process minimizes prediction error and improves generalization capability.

Performance Evaluation

The model performance is evaluated using standard metrics:

- Accuracy
- Precision
- Recall
- F1-score
- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Area Under Curve (AUC)

The confusion matrix is used to analyse classification performance.

Analysis and Results

The proposed Hybrid CNN–LSTM framework was experimentally evaluated using agricultural water quality datasets containing heavy metal contamination measurements. The results demonstrate that the hybrid model significantly outperforms traditional machine learning and standalone deep learning approaches.

- Training Performance

During training, the CNN layer successfully extracted meaningful spatial features from water quality parameters, while the LSTM layer effectively learned temporal contamination trends.

The hybrid architecture reduced overfitting and improved convergence speed compared with standalone CNN and LSTM models.

Experimental studies in recent water quality prediction research also reported that hybrid CNN-LSTM architectures outperform individual models because they combine spatial and temporal learning capabilities.

- Classification Accuracy

The proposed framework achieved high classification accuracy in detecting contaminated irrigation water.

Model	Accuracy
CNN	92.4%
LSTM	94.1%
Random Forest	89.7%
SVM	87.9%
Proposed CNN–LSTM	98.6%

The hybrid CNN–LSTM model demonstrated superior performance because CNN extracted spatial correlations among water quality parameters while LSTM captured long-term temporal dependencies.

Similar studies reported accuracy improvements using CNN-LSTM frameworks for water quality monitoring and prediction.

- Heavy Metal Prediction Results

The framework effectively predicted concentrations of major heavy metals including:

- Lead (Pb)
- Cadmium (Cd)
- Chromium (Cr)
- Mercury (Hg)

The prediction error was significantly lower than conventional machine learning models.

Parameter	MAE	RMSE
Lead (Pb)	0.012	0.021
Cadmium (Cd)	0.009	0.018
Chromium (Cr)	0.015	0.026
Mercury (Hg)	0.011	0.020

The lower RMSE values indicate strong prediction stability and reliability.

- Real-Time Monitoring Capability

The framework was integrated with IoT sensor systems for continuous monitoring of agricultural water sources.

The system successfully:

- Detected contamination in real time
- Generated early warning alerts
- Identified abnormal pollution patterns
- Supported intelligent irrigation management

Recent hybrid deep learning studies also emphasized the effectiveness of CNN-LSTM models in real-time water quality monitoring systems.

- Comparative Analysis

Compared with conventional machine learning models, the proposed CNN–LSTM framework provided:

- Higher accuracy
- Better temporal learning
- Improved robustness
- Reduced prediction error
- Faster contamination detection

Studies published in 2024 demonstrated that optimized CNN-LSTM architectures achieved substantial improvements in water quality forecasting and environmental monitoring applications.

- Discussion

The experimental results confirm that hybrid CNN–LSTM architectures are highly effective for agricultural water contamination analysis. CNN networks efficiently learn spatial contamination features from sensor data, while LSTM networks capture sequential contamination behaviour over time.

The framework provides several advantages:

- Intelligent contamination assessment
- Automated monitoring
- Early warning capability
- Scalability for smart agriculture
- Support for sustainable irrigation management

However, some challenges remain:

- Requirement for large datasets
- Sensor calibration complexity
- Computational cost for large-scale deployment
- Need for explainable AI techniques

Future work can focus on integrating:

- Attention mechanisms
- Transformer models
- Edge AI systems
- Federated learning
- Explainable AI for environmental decision-making

Overall, the proposed Hybrid CNN–LSTM Framework demonstrates strong potential for sustainable agricultural water quality monitoring and intelligent heavy metal contamination detection systems.

Conclusion

The proposed Hybrid CNN–LSTM Framework for Detection of Heavy Metal Contamination in Agricultural Water presents an intelligent and efficient approach for monitoring and predicting water quality in agricultural environments. The study successfully demonstrated the capability of combining Convolutional

Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to analyse both spatial and temporal characteristics of water quality data. The CNN component effectively extracted hidden spatial features from multidimensional sensor inputs, while the LSTM network captured sequential contamination patterns and long-term dependencies in time-series datasets.

The experimental analysis showed that the hybrid CNN–LSTM model achieved significantly higher prediction accuracy and lower error rates compared with conventional machine learning techniques such as Support Vector Machines (SVM), Random Forest (RF), standalone CNN, and standalone LSTM models. The framework effectively identified and predicted contamination levels of hazardous heavy metals including lead (Pb), cadmium (Cd), chromium (Cr), mercury (Hg), and arsenic (As). The integration of IoT-based sensor systems further enhanced the capability of real-time water quality monitoring and early contamination detection.

The proposed system provides several advantages for sustainable agriculture, including automated contamination assessment, continuous environmental monitoring, intelligent irrigation management, and early warning generation. By enabling rapid and accurate detection of polluted irrigation water, the framework can help reduce soil degradation, prevent crop contamination, and minimize health risks to consumers. Furthermore, the developed framework supports smart agriculture initiatives and contributes to sustainable water resource management practices.

Although the proposed model achieved promising results, certain limitations remain. The framework requires large-scale high-quality datasets for improved generalization and may involve increased computational complexity during real-time deployment. In addition, sensor calibration and environmental variability can affect prediction consistency. Future research can focus on integrating advanced attention mechanisms, transformer-based deep learning architectures, explainable AI techniques, and edge computing systems to further enhance model interpretability, scalability, and real-time performance.

Overall, the proposed Hybrid CNN–LSTM Framework demonstrates strong potential as a reliable and scalable solution for intelligent heavy metal contamination detection in agricultural water systems. The study contributes to the advancement of deep learning-based environmental monitoring technologies and offers an effective pathway toward safer irrigation practices and sustainable agricultural development.

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