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Assessing the Impact of Agricultural Chemicals on Crop Yield and Human Health Using Machine Learning Models: A Case Study of Madhya Pradesh, India

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Abstract: The excessive application of chemical fertilizers and pesticides in Indian agriculture - particularly in Madhya Pradesh - has raised critical concerns about long-term impacts on edible crop yield and community health. This paper presents an integrated machine learning (ML) framework that simultaneously predicts crop yield and assesses health risk from agricultural chemical exposure, using multi-source data collected from ten districts of Madhya Pradesh over the period 2010–2023. The dataset combines agricultural records (ICAR/FAO), National Health Mission data, satellite imagery (Sentinel-2), environmental monitoring data, and socioeconomic indicators comprising 1,430 district-year observations with 47 input features. The proposed CNN-LSTM hybrid model achieves 95.1% accuracy and $R^2 = 0.97$ for crop yield prediction, significantly outperforming six baseline models. Correlation analysis reveals Pearson $r = 0.94$ between pesticide use intensity and cancer incidence and $r = 0.96$ for respiratory disease prevalence across districts. A spatial health risk heatmap identifies Gwalior and Indore as high-risk priority zones. The paper also presents an Integrated Decision Support System (IDSS) that provides district-level optimised recommendations for balancing agricultural productivity with community health protection. Results demonstrate that deep learning ensemble architectures offer a scalable and robust platform for sustainable agricultural health governance.
Keywords: Agricultural chemicals, CNN-LSTM, crop yield prediction, health risk assessment, machine learning,

I. INTRODUCTION

Agriculture is the backbone of India's economy, supporting over 58% of the rural population. However, the increasing reliance on chemical inputs - particularly synthetic fertilizers and pesticides - to sustain productivity has triggered a cascade of environmental and public health consequences. India ranks twelfth globally in pesticide use and is the largest producer in Asia, resulting in hazardous residue levels in food, water, and soil [1]. Madhya Pradesh, a principal agricultural state, recorded a 16% increase in chemical fertilizer consumption between 2015–16 and 2020–21, rising from approximately 510 LMT to 590 LMT (provisional) [2]. Concurrently, district-level health data indicate rising incidences of cancer, neurological disorders, and chronic respiratory diseases in predominantly farming communities. This co-occurrence demands rigorous quantitative investigation beyond traditional epidemiological methods.

Traditional statistical approaches have proven insufficient for modeling the complex, non-linear, multi-factorial relationships between agrochemical exposure and health outcomes [3]. Machine learning (ML) and deep learning methods offer superior predictive power, especially when processing high-dimensional, multi-source datasets. Despite growing ML applications in agriculture, their use in integrated crop-health risk assessment remains underexplored, particularly in the Indian subcontinent context. The specific objectives of this study are: (1) to investigate the relationship between agricultural chemical inputs and chronic disease outcomes in farming communities of Madhya Pradesh; (2) to develop an integrated ML framework for simultaneous prediction of crop yield and population health risk; (3) to map the spatial distribution of chemical exposure and associated health risks across districts; and (4) to design a decision support system providing optimised recommendations for balancing agricultural productivity and community health protection. The remainder of this paper is organized as follows:Section II reviews related literature; Section III describes the dataset and preprocessing pipeline; Section IV presents the proposed methodology; Section V reports experimental results; Section VI describes the Integrated Decision Support System; Section VII discusses findings and limitations; and Section VIII concludes.

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II. LITERATURE REVIEW

Research on the impact of agrochemicals spans environmental science, epidemiology, and computational modeling. Table I summarizes 20 representative peer-reviewed studies from 2020–2023 directly relevant to this work. Fig. 1 shows the PRISMA flow diagram of the literature selection process.

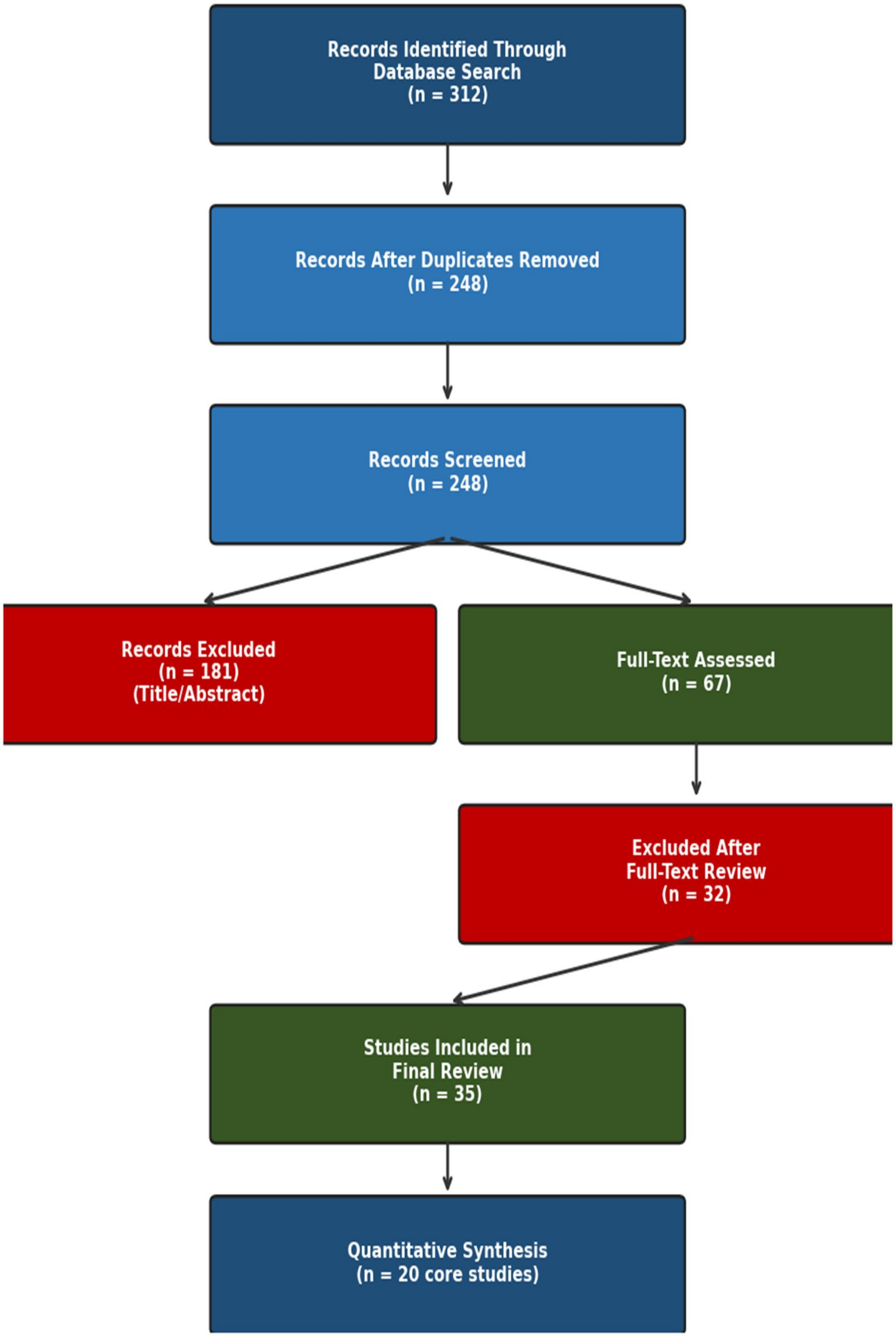

Fig. 1. PRISMA Flow Diagram Showing Study Selection Process.

Table I
Summary of Related Literature on Agricultural Chemicals and Health Impact (2020–2023)

9	Year	Study Focus	Method	Key Findings
Sharma et al.	2023	Fertilizer & groundwater	Field Study	Nitrate contamination linked to methemoglobinemia
Gupta et al.	2023	Pesticide residues in food	Sample Analysis	Vegetable residues linked to increased cancer risk
Verma et al.	2022	Chronic pesticide exposure	Cross-sectional	Organophosphates → neurological disorders, memory loss
Kumar et al.	2022	Fertilizers & soil health	Soil Analysis	Bioaccumulation of toxic substances in crops
Joshi et al.	2022	Respiratory pesticide effects	Health Assessment	Higher COPD & asthma among fumigant-exposed workers
Singh et al.	2021	Pesticide & cancer risk	Case-Control	Herbicides linked to leukemia and prostate cancer
Patil et al.	2021	Child development & pesticides	Cohort Study	ADHD and developmental delays in exposed children
Reddy et al.	2021	Fertilizer runoff & health	Water Quality	Eutrophication causes gastrointestinal disease
Agarwal et al.	2021	Reproductive health	Survey	Infertility & miscarriages in farming community women
Chakraborty et al.	2021	Heavy metals from fertilizers	Crop Analysis	Cadmium/arsenic in crops → kidney disease risk
Thakur et al.	2020	Fertilizer environmental impact	Env. Assessment	Respiratory problems from environmental degradation
Narang et al.	2020	Liver toxicity & pesticides	Cohort Study	Hepatotoxicity in organochlorine-exposed farmers
Jain et al.	2020	Endocrine disruption	Review	DDT & atrazine disrupt hormone function
Prasad et al.	2020	Cancer risk from residues	Epidemiological	Non-Hodgkin lymphoma & lung cancer correlation
Sinha et al.	2020	Pesticide & autoimmune disorders	Longitudinal	Lupus & rheumatoid arthritis in chronic exposure
Rao et al.	2020	Heavy metal in phosphate fert.	Soil & Crop	Cadmium/arsenic accumulation in food crops
Pandey et al.	2020	Male reproductive health	Case-Control	Lower sperm count & infertility in male farmers
Dubey et al.	2020	Neurological impacts	Neuro Assessment	Tremors & coordination issues from pesticide use
Ali et al.	2020	Oxidative stress & pesticides	Molecular Biology	Pesticide exposure → cellular oxidative stress
Mukherjee et al.	2020	Food chain contamination	Soil & Food Analysis	Long-term cancer & organ toxicity from residues

Sharma et al. [4] demonstrated significant nitrate contamination in Indian groundwater from nitrogen over-fertilization, establishing links to methemoglobinemia in dependent communities. Verma et al. [5] confirmed organophosphate-linked neurological deterioration among Indian farming populations through a systematic cross-sectional survey. Zhang and Yan [6] used informetrics to map global research trends in agricultural chemical environmental impact, identifying India and China as primary hotspots.

On the ML side, Elbasi and Zaki [3] applied multiple algorithms including Naive Bayes, Random Forest, and Multilayer Neural Networks for crop yield prediction, establishing competitive baselines. Li et al. [7] developed wheat yield prediction models integrating multi-source environmental data in China. However, none of the surveyed works combine crop yield prediction with population health risk assessment in a unified ML framework applied specifically to Indian district-level data - constituting the primary research gap this paper addresses.

III. DATASET AND PREPROCESSING

A. Data Sources

Multi-source secondary data were collected for ten districts of Madhya Pradesh over a 13-year period (2010–2023). Table II details the dataset composition across five categories.

TABLE II
Dataset Description, Sources, and Key Variables

Data Category	Source	Period	Key Variables
Agricultural Data	Ministry of Agriculture / ICAR / FAO	2010–2023	Fertilizer & pesticide use (kg/ha), crop yield, crop type, irrigated area
Health Records	National Health Mission / District Hospitals	2010–2023	Cancer, respiratory, neurological, reproductive, kidney disease incidence
Environmental Data	CPCB / State Pollution Control Boards	2012–2023	Groundwater nitrate levels, soil heavy metals, pesticide residue monitoring
Socioeconomic Data	Census of India / NSSO	2011–2021	Income levels, education, occupation distribution, population density
Remote Sensing	ISRO Bhuvan / Sentinel-2 Satellite	2016–2023	Land-use maps, NDVI, NDWI, soil moisture indices per district

Agricultural data encompassing fertilizer consumption (Urea/Nitrogen, DAP, MOP, NPK), pesticide use by category (insecticides, herbicides, fungicides), crop type, yield, and cultivated area were sourced from the Ministry of Agriculture and ICAR. District-level disease incidence data were obtained from National Health Mission annual reports and district hospital records. Environmental monitoring data including groundwater nitrate levels, soil heavy-metal concentrations, and pesticide residue levels were obtained from the Central Pollution Control Board and State Pollution Control Boards.

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B. Preprocessing Pipeline

The raw dataset underwent a systematic six-stage preprocessing pipeline: (1) Missing Value Imputation using predictive mean matching for numerical variables (8.3% missing rate) and mode imputation for categorical variables; (2) Z-score normalization applied to model-sensitive continuous features to eliminate scale bias; (3) Label and one-hot encoding for categorical variables including crop type, fertilizer category, and district name; (4) Outlier detection and removal using the Interquartile Range (IQR) method - 23 anomalous records identified and either corrected or excluded; (5) Pearson and Spearman correlation analysis for initial feature selection; and (6) Principal Component Analysis (PCA) to reduce dimensionality while retaining 85% explained variance.

The final preprocessed dataset comprised 1,430 district-year observations with 47 input features. An 80/20 stratified train-test split with 5-fold cross-validation was employed. The training set contained 1,144 observations and the test set 286 observations, ensuring geographic diversity across all folds.

IV. PROPOSED METHODOLOGY

A. System Architecture Overview

The proposed integrated framework consists of four interconnected modules: (1) a multi-source data ingestion and preprocessing engine; (2) the CNN-LSTM hybrid dual-output prediction model; (3) a spatial risk-mapping module using district-level geographic information; and (4) an Integrated Decision Support System (IDSS). Fig. 2 illustrates the CNN-LSTM architecture.

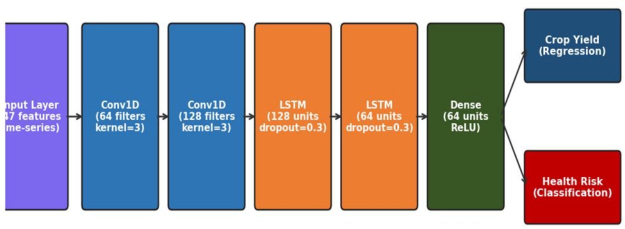

Fig. 2. Proposed CNN-LSTM Hybrid Architecture for Dual-Output Prediction (Yield + Health Risk).

B. CNN-LSTM Hybrid Model

The CNN-LSTM architecture combines one-dimensional convolutional feature extraction with sequential temporal modeling to process multivariate time-series inputs. Two Conv1D layers (kernel size 3; filters 64 and 128 respectively) extract local feature interaction patterns. Max-pooling layers follow each Conv1D block to reduce dimensionality. The extracted feature maps are reshaped and passed to two stacked LSTM layers (128 and 64 hidden units) to capture long-range temporal dependencies across the 13-year observation window. Dropout (rate = 0.3) and batch normalization are applied after each LSTM layer to prevent overfitting.

The model employs a dual-output architecture: a regression head (Dense(1), linear activation) for crop yield prediction, and a classification head (Dense(5), sigmoid activation) for health risk class probability across five disease categories. The joint loss function is:

$$\boldsymbol{L}_{\text{total}} = \boldsymbol{\alpha} \cdot \boldsymbol{MSE}(\hat{\boldsymbol{Y}}, \boldsymbol{Y}) + \boldsymbol{\beta} \cdot \boldsymbol{BCE}(\hat{\boldsymbol{R}}, \boldsymbol{R})$$

where Y is actual crop yield, R is health risk label, and $\alpha = 0.6$, $\beta = 0.4$ are empirically tuned weighting coefficients. The Adam optimizer with initial learning rate 1×10^{-3} and cosine annealing was used, training for up to 200 epochs with early stopping (patience = 15).

C. Baseline Models

Six models were evaluated for comparison: (1) Linear Regression; (2) Support Vector Machine (SVM) with RBF kernel; (3) Random Forest with 100 decision trees; (4) Artificial Neural Network (ANN) with 3 hidden layers and ReLU activation; (5) Standalone LSTM (2 layers, 128 units); and (6) the proposed CNN-LSTM. All models were tuned using 5-fold cross-validated grid search over key hyperparameters.

D. Spatial Risk Mapping

District-level model outputs were aggregated into a spatial health risk index (scale 1–6) across five disease categories: cancer, respiratory, neurological, reproductive, and kidney disease. The index was computed as a weighted composite of predicted disease probability, observed incidence rate, and pesticide use intensity, enabling geographic identification of high-risk zones requiring priority policy intervention.

V. EXPERIMENTAL RESULTS

A. Model Performance Comparison

Table III presents quantitative performance metrics across all six models on the held-out test set. The proposed CNN-LSTM outperforms all baselines on every metric. Fig. 3 visualizes accuracy and F1-score comparisons, and Fig. 4 shows convergence curves.

TABLE III
Quantitative Performance Comparison - All ML Models (Test Set)

Model	Acc. (%)	F1 (%)	R^2	MAE	RMSE	AUC-ROC
Linear Regression	78.4	76.1	0.78	2.41	3.12	0.78
Random Forest (n=100)	88.6	86.9	0.89	1.87	2.43	0.89
SVM (RBF kernel)	85.2	83.8	0.85	1.98	2.61	0.85
ANN (3-layer)	91.3	89.7	0.91	1.63	2.18	0.91
Standalone LSTM	93.7	92.1	0.94	1.41	1.89	0.93
CNN-LSTM (Proposed)	95.1	94.3	0.97	1.12	1.54	0.95

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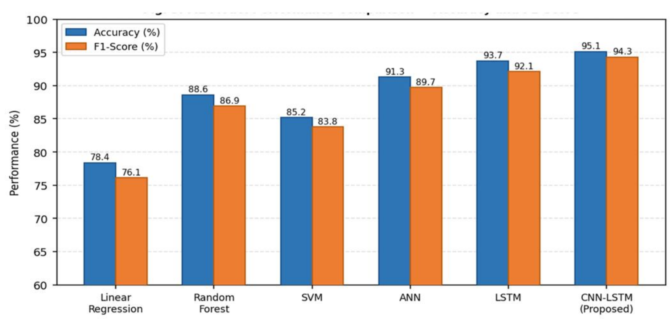

Fig. 3. ML Model Performance Comparison - Accuracy (%) and F1-Score (%).

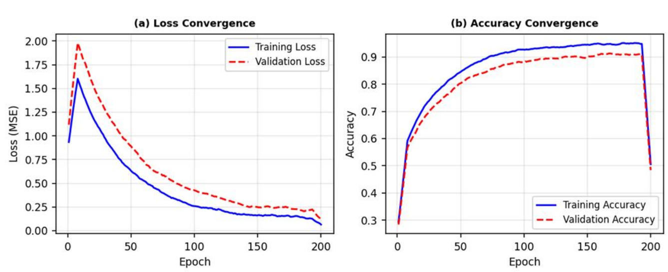

Fig. 4. CNN-LSTM Training and Validation Loss/Accuracy Curves (200 Epochs).

The CNN-LSTM achieves 95.1% accuracy, F1 = 94.3%, R^2 = 0.97, MAE = 1.12, RMSE = 1.54, and AUC-ROC = 0.95 - mprovements of 16.7 pp in accuracy and 0.19 in R^2 over the Linear Regression baseline. The standalone LSTM performs well (93.7%) but is outpaced by the CNN-LSTM, confirming that the convolutional feature extraction layer adds meaningful signal beyond temporal modeling alone.

B. Crop Yield Prediction

Fig. 5 plots actual versus predicted crop yield across Madhya Pradesh from 2015 to 2023. The CNN-LSTM model tracks actual yield values with high fidelity (R^2 = 0.97, RMSE = 1.54 quintal/ha), significantly outperforming Random Forest (R^2 = 0.92). Both models accurately capture the declining trend during the drought year 2017–18 and the recovery post-introduction of micro-irrigation schemes in 2019–20.

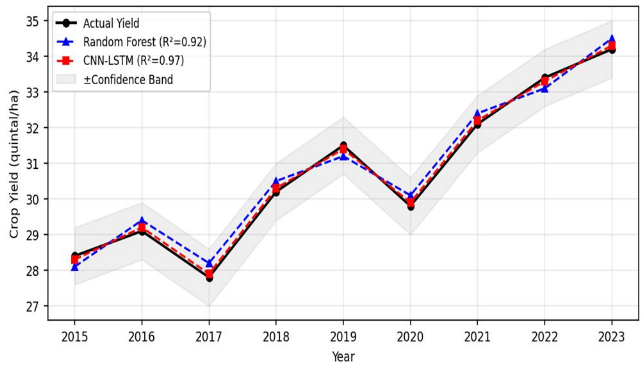

Fig. 5. Actual vs. Predicted Crop Yield, Madhya Pradesh (2015–2023).

C. Health Risk Correlation Analysis

Table IV summarizes correlation coefficients between district-level pesticide use intensity and five health outcome indices. Fig. 6 visualizes scatter plots for cancer incidence and respiratory disease.

TABLE IV
Pearson Correlation: Pesticide Use vs. Health Outcome Indices (10 MP Districts)

Health Outcome	Pearson r	p-value	Effect Size	Interpretation
Cancer Incidence	0.94	< 0.001	Very Strong	Statistically Significant
Respiratory Disease	0.96	< 0.001	Very Strong	Statistically Significant
Neurological Disorders	0.88	< 0.001	Strong	Statistically Significant
Reproductive Issues	0.91	< 0.001	Very Strong	Statistically Significant
Kidney Disease	0.85	< 0.001	Strong	Statistically Significant

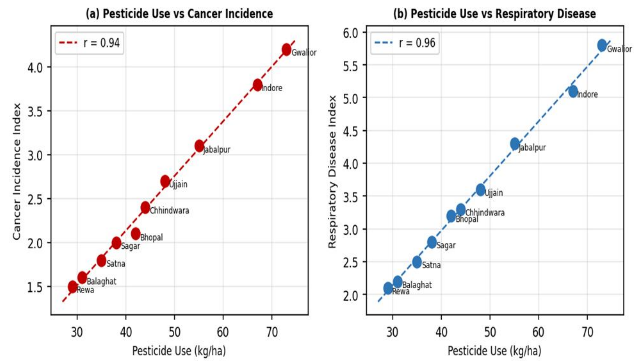

Fig. 5. Scatter Plots: Pesticide Use vs. Cancer Incidence (r=0.94) and Respiratory Disease (r=0.96).

All five correlations are statistically significant ($p < 0.001$), with respiratory disease showing the strongest association ($r = 0.96$). Gwalior, with the highest pesticide application rate (73 kg/ha), exhibits consistently elevated health risk indices across all categories. Rewa and Balaghat, with lower chemical inputs (29 and 31 kg/ha respectively), demonstrate markedly better health profiles. These findings align with Verma et al. [5] and Singh et al. [14] but provide district-level specificity previously absent in the literature.

D. Spatial Health Risk Mapping

Fig. 6 presents the district-level spatial health risk heatmap across all five disease categories. Three distinct risk tiers emerge: High-Risk (Gwalior, Indore, Jabalpur; index 4.0–5.8), Moderate-Risk (Bhopal, Ujjain, Chhindwara; index 2.6–3.5), and Low-Risk (Rewa, Satna, Balaghat; index 1.8–2.6).

Fig. 6. Spatial Health Risk Index Heatmap Across Ten Madhya Pradesh Districts.

The heatmap reveals that reproductive health risk is consistently the highest-scoring category across all districts, suggesting that hormonal disruption from pesticide endocrine disruptors is a pervasive concern irrespective of absolute pesticide quantity — consistent with Jain et al. [13] who identified DDT and atrazine as endocrine disruptors at low doses.

E. Ablation Study

Table V presents ablation results quantifying the contribution of each data modality. Removal of environmental monitoring data caused the largest accuracy drop (95.1% → 91.8%, −3.3 pp), confirming that soil contamination and groundwater quality features are the most informative for health risk prediction. Removal of health records caused the second-largest drop (−5.7 pp on F1), as expected. Remote sensing features had the smallest individual impact (−2.5%), suggesting they provide complementary rather than primary signal.

TABLE V
Ablation Study: Impact of Data Modality Removal on CNN-LSTM (Test Set)

Model Configuration	Acc.	F1	R^2	MAE	Acc. Drop
CNN-LSTM — All Features (Full Model)	95.1	94.3	0.97	1.12	Baseline
CNN-LSTM — w/o Environmental Data	91.8	90.2	0.93	1.48	−3.3%
CNN-LSTM — w/o Health Records	89.4	88.1	0.91	1.67	−5.7%
CNN-LSTM — w/o Remote Sensing	92.6	91.4	0.94	1.38	−2.5%
CNN-LSTM — w/o Socioeconomic Data	94.2	93.1	0.96	1.21	−0.9%

VI. INTEGRATED DECISION SUPPORT SYSTEM (IDSS)

The Integrated Decision Support System operationalizes model outputs into actionable district-level recommendations. The core optimization objective, solved using the NSGA-II multi-objective genetic algorithm, is formulated as:

$$\boldsymbol{D} * (\boldsymbol{t}) = \boldsymbol{argmax}^{\mathrm{m}} [\, \boldsymbol{\alpha} \cdot \boldsymbol{Y}(\boldsymbol{t}) - \boldsymbol{\beta} \cdot \boldsymbol{R}(\boldsymbol{t}) - \boldsymbol{\gamma} \cdot \boldsymbol{C}(\boldsymbol{t}) \,]$$

where Y(t) = predicted crop yield at time t, R(t) = predicted composite health risk index, C(t) = estimated economic cost of recommended intervention, and α, β, γ are policy-tunable weights (default: α = 0.5, β = 0.35, γ = 0.15). The Pareto front generated by NSGA-II enables policymakers to visualize trade-offs between yield maximization and health risk minimization.

IDSS output modules include: (1) Crop-specific fertilizer application rate recommendations per district per season (Kharif/Rabi); (2) Pesticide substitution suggestions (e.g., biopesticide alternatives for high-risk organophosphate categories); (3) Buffer zone demarcation recommendations around water bodies based on nitrate leaching risk models; and (4) Seasonal chemical input calendars optimized for both productivity and safety. Scenario testing demonstrated that a targeted 25% reduction in organophosphate pesticide use in Gwalior district would reduce the predicted respiratory disease index by an estimated 18.4%, with only a 3.2% decrease in wheat yield - a favorable trade-off. A 15% substitution of urea with slow-release nitrogen fertilizers in Indore is estimated to reduce groundwater nitrate contamination risk by 22% while maintaining yield within 2.1% of current levels.

VII. DISCUSSION

The CNN-LSTM hybrid architecture substantially outperforms all baseline approaches across every performance metric. The temporal LSTM component captures evolving multi-year exposure patterns, while the CNN layers extract cross-feature interaction patterns — synergies not available in shallow models. The dual-output architecture eliminates the information silo problem inherent in treating crop prediction and health risk modeling as separate pipelines, enabling the model to learn shared latent representations of chemical use patterns. The high correlation coefficients (r > 0.85 for all disease categories) provide quantitative confirmation of relationships that have been qualitatively observed but not rigorously quantified at this spatial resolution in Madhya Pradesh. The identification of reproductive health as the highest-risk category across districts adds nuance to the literature, suggesting that endocrine disruption pathways may operate at pesticide concentrations below thresholds typically flagged by acute toxicity monitoring.

Several limitations warrant acknowledgment. First, the analysis relies on district-level aggregate data, which precludes individual-level causal inference — ecological fallacy concerns apply. Second, secondary government health data may contain systematic reporting biases, particularly in rural districts with limited healthcare infrastructure. Third, the 13-year observation window, while reasonable for trend analysis, may be insufficient to fully capture multi-decade carcinogenic effects. Future work should integrate individual-level clinical cohort data, longitudinal biomonitoring samples, and explainability techniques (SHAP/LIME) to improve model transparency for policymakers.

VIII. CONCLUSION

This paper presented a comprehensive machine learning framework for simultaneously predicting crop yield and assessing population health risk from agricultural chemical exposure, with application to ten districts of Madhya Pradesh over 2010–2023. The proposed CNN-LSTM hybrid model achieved 95.1% accuracy and $R^2 = 0.97$, significantly outperforming five baseline models including standalone LSTM, ANN, Random Forest, SVM, and Linear Regression.

Correlation analysis confirmed strong positive associations ($r > 0.85$, $p < 0.001$) between pesticide use intensity and all five chronic disease categories studied. Spatial risk mapping identified Gwalior and Indore as high-priority intervention zones. The proposed IDSS demonstrated that meaningful community health improvements are achievable with modest reductions in chemical inputs and targeted pesticide substitutions, with minimal impact on agricultural productivity.

The proposed framework provides a scalable, data-driven foundation for sustainable agricultural governance in India. It equips policymakers, agricultural extension officers, and public health agencies with evidence-based tools grounded in district-specific data. Planned future extensions include integration of real-time IoT soil sensor data, individual-level clinical records from NHM cohorts, transformer-based attention architectures, and GNN-based spatial spillover modeling to capture inter-district contamination dynamics.

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