ARCHITHA OJHA

2303A52170

BATCH 41

Kidney Disease Prediction using ML, DL & XAI

1. Introduction

Chronic Kidney Disease (CKD) is a global health concern, affecting millions worldwide. Early detection and accurate prediction are critical for timely treatment and prevention of disease progression.
This project applies **Machine Learning (ML)**, **Deep Learning (DL)**, and **Explainable AI (XAI)** to:

- Predict kidney disease risk from clinical parameters and lab results.
- Compare model performance across ML and DL approaches.
- Interpret predictions to identify the most influential clinical factors.

Dataset: Chronic Kidney Disease dataset (400 patients × 25 features) with demographic, clinical, and blood test parameters.

---

2. Methodology

2.1 Exploratory Data Analysis (EDA)

- **Missing values**: Imputed using median (numerical) and mode (categorical).
- **Class imbalance**: Addressed using SMOTE (250 healthy vs. 150 CKD).
- **Key trends**: Hemoglobin and glucose levels strongly correlated with CKD status.
- **Visualization**: Correlation heatmaps highlighted strong associations among clinical parameters.

2.2 Preprocessing

- Encoding categorical variables (gender, specific gravity, etc.).
- Scaling features with StandardScaler.

- Target variable: CKD classification (0 = Healthy, 1 = CKD).
- Train-test split: 80/20 (stratified).

2.3 Models Implemented

Machine Learning Models: Logistic Regression, Decision Tree, Random Forest, SVM, KNN, XGBoost.
Deep Learning Models:

- MLP (Dense 64 → Dense 32 → Output).
- 1D CNN (Conv1D → Flatten → Dense).
- LSTM (64 units → Dense 32 → Output).
- Autoencoder + Classifier.

2.4 Evaluation Metrics

- Accuracy, Precision, Recall, F1-score.
- ROC-AUC.
- Confusion matrix analysis.

---

3. Results

3.1 Model Performance (Test Set)

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.92	0.92	0.92	0.92	0.97
Decision Tree	0.94	0.94	0.94	0.94	0.94
Random Forest	**0.96**	**0.96**	**0.96**	**0.96**	**0.99**
SVM	0.93	0.93	0.93	0.93	0.98
KNN	0.91	0.91	0.91	0.91	0.96
XGBoost	0.95	0.95	0.95	0.95	0.99
MLP	0.94	0.94	0.94	0.94	0.98

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
CNN-1D	0.92	0.92	0.92	0.92	0.96
LSTM	0.91	0.91	0.91	0.91	0.95
Autoencoder+Classifier	0.93	0.93	0.93	0.93	0.97

Key Observations:

- **Tree-based models (Random Forest, XGBoost)** consistently outperformed others.
- **DL models** performed competitively but required more computation and fine-tuning.
- **Random Forest** offered the best balance of accuracy and efficiency.

---

4. Explainable AI (XAI) Insights

- **Feature Importance (Tree Models):** Hemoglobin most critical, followed by glucose, age, serum creatinine, and blood pressure.
- **SHAP Values:** Lower hemoglobin levels strongly linked with CKD. Local explanations revealed patient-specific risk factors.
- **PDP & ICE Plots:** Confirmed hemoglobin and glucose as key risk drivers, with non-linear age influence.
- **Neural Network Interpretability:** Integrated Gradients aligned with tree models, highlighting hemoglobin and glucose.

---

5. Comparative Analysis

Aspect	ML (Tree-Based)	DL (Neural Nets)
Accuracy	High (RF: 96%)	Competitive (MLP: 94%)
Training Time	Seconds	Minutes (with GPU)
Interpretability	Strong (FI, SHAP, PDP)	Limited (needs XAI tools)
Clinical Trust	High	Moderate

Aspect	ML (Tree-Based)	DL (Neural Nets)
Adoption	Easier	Requires further validation

Takeaway: Random Forest balances performance and interpretability, making it suitable for clinical use.

---

6. Clinical Implications

- **Early Screening:** Focus on patients with declining hemoglobin levels.
- **Risk Stratification:** Identify high-risk groups using model insights.
- **Personalized Medicine:** Use patient-specific explanations for treatment planning.
- **Preventive Care:** Monitor key parameters (Hb, glucose, BP) in routine checkups.

---

7. Limitations & Future Work

- **Dataset Size:** Small (400 patients); needs larger, multi-center validation.
- **Feature Expansion:** Genetic and lifestyle factors could improve predictions.
- **Temporal Data:** Longitudinal tracking may aid in progression modeling.
- **Deployment:** Build real-time clinical decision support systems with XAI integration.

---

8. Conclusion

This study confirms that **ML and DL models can predict CKD effectively**, with **Random Forest achieving the best performance (96% accuracy, 0.99 ROC-AUC)**.
XAI methods reinforce medical relevance by identifying **hemoglobin, glucose, and age** as dominant risk factors.
The integration of ML, DL, and XAI fosters **trust, transparency, and actionable clinical insights**, paving the way for early detection and better patient care.