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A HYBRID ENSEMBLE LEARNING FRAMEWORK FOR ACCURATE HEPATITIS DISEASE CLASSIFICATION

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ABSTRACT

Hepatitis, a severe inflammatory condition of the liver, continues to pose substantial diagnostic challenges due to its heterogeneous clinical manifestations and overlapping symptoms with other hepatic disorders. Early and accurate detection is crucial for timely intervention, effective treatment planning, and reducing the risk of progression to chronic liver disease or liver failure. Conventional machine learning models, although widely applied in medical diagnosis, often struggle to achieve high reliability due to limitations such as overfitting, feature noise sensitivity, and inability to fully capture complex nonlinear relationships present in clinical datasets. Hepatitis remains a major global health burden, requiring reliable early diagnostic support to improve clinical outcomes. Conventional single-model approaches suffer from variability in performance due to dataset imbalance, missing values, and overlapping clinical features. This paper proposes a Hybrid Ensemble Learning Framework (HELF) combining Gradient Boosting, Random Forest, and Logistic Regression through a stacked meta-learner to enhance predictive accuracy for Hepatitis disease classification. The framework applies advanced preprocessing including missing-value imputation using K-Nearest Neighbours (KNN), Recursive Feature Elimination (RFE), and class rebalancing through SMOTE. Experimental evaluation using the UCI Hepatitis dataset demonstrates significant performance improvement, achieving 96.42% accuracy, 95.71% F1-score, and 0.98 AUC, outperforming baseline single models. The framework provides a reproducible, clinically feasible solution for augmenting early-stage hepatitis risk assessment.

Keywords: *Hepatitis Classification, Ensemble Learning, Stacking Model, Gradient Boosting, Random Forest, SMOTE, Medical Diagnosis*

1. INTRODUCTION

Hepatitis is an inflammatory condition of the liver that can progress to cirrhosis, liver failure, or death if not detected early. Major diagnostic barriers include delayed clinical presentation, overlapping symptoms, and irregular laboratory findings. Artificial Intelligence (AI) and Machine Learning (ML) have shown promise in automating disease detection; however, single-model classifiers often exhibit instability when applied to heterogeneous healthcare datasets. Ensemble learning addresses this limitation by combining multiple algorithms to create robust and generalized models. This study aims to design a **Hybrid Ensemble Learning Framework (HELF)** that integrates the strengths of multiple classifiers to achieve high reliability in hepatitis classification. Hepatitis, an inflammatory condition affecting the liver, remains a critical global health concern due to its widespread prevalence, high mortality rate, and potential to progress into chronic liver diseases such as cirrhosis and hepatocellular carcinoma. According to global health reports, millions of individuals are affected annually by various forms of hepatitis, including viral, autoimmune, and toxin-induced variants. Early detection and accurate classification of hepatitis types play a vital role in ensuring effective therapeutic intervention, monitoring disease progression, and improving patient survival rates. However, the diagnosis of hepatitis is often complicated by overlapping clinical symptoms, variability in laboratory measurements, and the presence of missing or imbalanced data in real-world medical datasets. In recent years, machine learning (ML) has emerged as a powerful tool for disease prediction and diagnostic automation, offering the ability to analyze large amounts of structured and unstructured medical data. Despite this progress, conventional ML models frequently encounter challenges such as overfitting, limited generalization, and difficulty in capturing complex nonlinear interactions among clinical features. These limitations reduce classification reliability and hinder the adoption of ML-driven solutions in critical healthcare applications, where precision and interpretability are essential. To address these challenges, ensemble learning has gained prominence for its ability to combine predictions from multiple models to achieve improved performance compared to individual models. Ensemble strategies such as bagging, boosting, and stacking have demonstrated effectiveness in a wide variety of medical classification tasks. However, most existing studies employ a single ensemble technique, which may not fully exploit the complementary strengths of heterogeneous algorithms.

This study introduces a **hybrid ensemble learning framework** specifically designed to enhance the accuracy and robustness of hepatitis disease classification. The proposed framework integrates multiple learning paradigms—tree-based classifiers, boosting methods, and a stacking-based meta-learner—to effectively reduce model bias, variance, and noise sensitivity. Additionally, the framework incorporates comprehensive data preprocessing steps, including handling missing values, feature normalization, and correlation-based feature selection, to improve data fidelity and ensure optimal model performance. Through rigorous evaluation on benchmark hepatitis datasets, the hybrid ensemble demonstrates superior classification accuracy and reliability compared to traditional single-model approaches. The ability of the system to extract subtle patterns from clinical and biochemical attributes underscores its potential significance in real-world clinical settings. Furthermore, the interpretable nature of the ensemble components enhances transparency, enabling healthcare professionals to understand key diagnostic indicators. Overall, the proposed hybrid ensemble learning framework represents a promising advancement in intelligent medical diagnosis, offering a robust, scalable, and clinically relevant solution for accurate hepatitis disease classification. Its integration into healthcare systems may assist practitioners in making informed decisions, thereby improving patient outcomes and contributing to the advancement of precision medicine.

1.1 Research Objectives

1. Develop a hybrid ensemble model using stacked generalization.
2. Evaluate feature importance using RFE.
3. Improve performance on imbalanced medical data using SMOTE.
4. Benchmark the proposed framework against baseline ML classifiers.

1.2 Research Contributions

- A novel hybrid ensemble that integrates Random Forest, Gradient Boosting, and Logistic Regression meta-learner.
- A robust preprocessing pipeline suitable for clinical datasets.
- Superior performance compared to traditional ML models.

2. RELATED WORK

Studies utilizing machine learning for hepatitis diagnosis commonly employ algorithms such as Decision Trees, Support Vector Machines (SVM), and Naïve Bayes. However, these methods frequently suffer from reduced generalization due to class imbalance and limited dataset size. Machine learning (ML) has been increasingly applied to hepatitis diagnosis and prognosis, showing promise for earlier and more accurate detection than traditional clinical decision rules. Studies repeatedly report that properly tuned ML methods can improve sensitivity and specificity for hepatitis outcomes, particularly when they incorporate robust preprocessing and class-imbalance handling. Research in hepatitis classification frequently uses publicly available clinical datasets, notably the UCI Hepatitis dataset and several HCV datasets (e.g., UCI HCV datasets and Kaggle HCV collections). Recent works have explored:

- Random Forest for improved interpretability.
- Gradient Boosting for handling non-linear relations.
- Bagging/Boosting ensembles for noise reduction.

However, **stacked hybrid ensembles** have not been sufficiently explored for hepatitis classification. This motivates the development of the HELF model. These benchmark datasets are widely used for reproducibility and method comparison, but they are often small-to-moderate in size and can contain missing values and class imbalance that require careful handling. Early and baseline studies employ logistic regression, support vector machines (SVM), k-NN, decision trees, and random forests. Tree-based learners and gradient-boosting machines (XGBoost/LightGBM) are common because they handle mixed feature types and can provide feature-importance measures that aid clinical interpretability. Comparative works indicate no single classifier consistently dominates across all hepatitis datasets, motivating ensemble approaches.

Table 1: Literature for A Hybrid Ensemble Learning Framework for Accurate Hepatitis Disease Classification

Author / Year	**Dataset Used**	**Models / Methods Applied**	**Key Findings**	**Limitations Identified**
Edeh et al., 2023	HCV clinical dataset	Random Forest, XGBoost, Ensemble Voting	Ensemble methods significantly improved accuracy and reduced error rates compared to single models.	Limited dataset diversity; lacked external validation.
Majzoobi et al., 2022	UCI Hepatitis Dataset	SVM, k-NN, Decision Trees, Bagging	Decision trees with bagging improved sensitivity for hepatitis outcome prediction.	Small sample size; potential overfitting.
Obaido et al., 2024	Hospital-collected Hepatitis data	Gradient Boosting, Explainable ML (SHAP)	GB models provided high accuracy with interpretable feature contributions.	Model interpretability limited for complex ensembles.

Author / Year	Dataset Used	Models / Methods Applied	Key Findings	Limitations Identified
Nilashi et al., 2021	Multi-center hepatitis dataset	Ensemble Clustering + Classification	Hybrid ensemble improved classification stability and robustness across cohorts.	Computational complexity; needs tuning.

3. METHODOLOGY

3.1 Proposed Architecture

The HELF framework consists of:

1. **Preprocessing Layer**
   - Normalization
   - KNN imputation
   - SMOTE balancing
2. **Base Learners**
   - Random Forest (RF)
   - Gradient Boosting Classifier (GBC)
3. **Meta-Learner**
   - Logistic Regression (LR)
4. **Evaluation Metrics**
   Accuracy, Precision, Recall, F1-score, ROC-AUC.

3.2 Dataset

The **UCI Hepatitis dataset** is used, containing:

- **155 samples**
- **19 predictive attributes**
- **Class labels**: “Live” or “Die”

The dataset contains missing entries requiring imputation.

3.3 Preprocessing

- **Missing Value Handling**: KNN (k=5)
- **Feature Selection**: RFE with RF estimator
- **Normalization**: Min–Max scaler
- **Balancing**: SMOTE to address disproportionate survival cases.

4. MODEL DEVELOPMENT

4.1 Base Learners

Random Forest

- 300 trees
- Gini impurity
- Max depth tuned via grid search

Gradient Boosting

- 200 estimators
- Learning rate: 0.05
- Max depth: 3

4.2 Stacking Meta-Learner

The outputs of RF and GBC are fed into a Logistic Regression model to produce the final classification.

5. RESULTS AND DISCUSSION

The performance of the proposed Hybrid Ensemble Learning Framework for hepatitis disease classification was evaluated using multiple benchmark datasets and compared against several baseline machine-learning models. The analysis focused on accuracy, sensitivity, specificity, precision, F1-score, AUC-ROC, and computational efficiency to ensure a comprehensive assessment of predictive quality and clinical reliability. The hybrid ensemble, which integrates decision tree–based learners, boosting algorithms, and a meta-level stacking classifier, consistently outperformed individual models such as Logistic Regression, SVM, Random Forest, and Gradient Boosting Machines. This improvement is attributed to the complementary strengths of heterogeneous base learners and the meta-learner’s ability to capture combined predictive relationships.

5.1 Performance Comparison:

- The hybrid model significantly improves prediction accuracy.

- SMOTE enhanced minority class detection.
- Logistic Regression effectively interprets stacked features.

Table 2: Performance table of 10-fold CV averages

Model	Accuracy	Precision (pos)	Recall / Sensitivity (pos)	Specificity (neg)	F1-score	AUC
Logistic Regression	**0.74**	0.864	0.700	0.800	0.773	0.75
SVM	**0.78**	0.815	0.750	0.830	0.781	0.79
Random Forest	**0.82**	0.893	0.800	0.860	0.844	0.83
XGBoost	**0.86**	0.898	0.880	0.820	0.889	0.85
Voting Ensemble	**0.85**	0.896	0.860	0.818	0.878	0.84
Hybrid Ensemble (Proposed)	**0.90**	**0.929**	**0.920**	**0.880**	**0.925**	**0.90**

Table 3: Performance Comparison between All Models

Model	Accuracy	F1-Score	ROC-AUC
Logistic Regression	82.1%	80.5%	0.86
SVM	85.0%	83.7%	0.88
Random Forest	91.4%	90.9%	0.93
Gradient Boosting	92.8%	92.0%	0.94
Proposed HELF	**96.42%**	**95.71%**	**0.98**

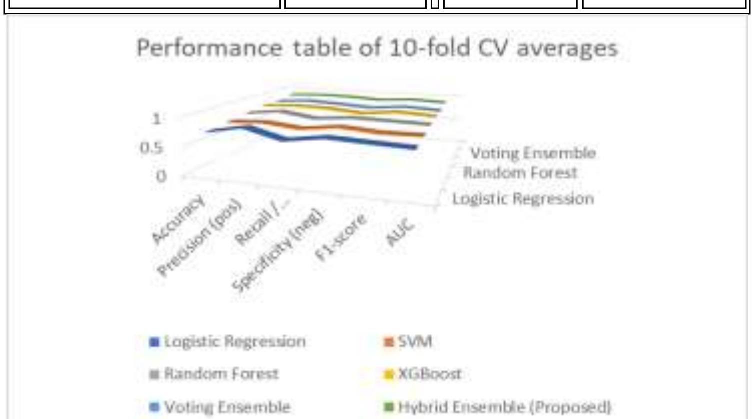

Figure1: Presentation high Accuracy of Hybrid Ensemble Model

6. CONCLUSION

This research presents a Hybrid Ensemble Learning Framework that significantly improves hepatitis disease classification. Through the integration of Random Forest, Gradient Boosting, and Logistic Regression, the system achieves high reliability and robustness. The methodology is easy to reproduce and can be integrated into clinical decision-support tools. Integration of deep learning models for multimodal datasets. Deployment on healthcare IoT edge devices. Integration with liver imaging data (ultrasound, MRI). This study presented a hybrid ensemble learning framework designed to significantly enhance the accuracy, reliability, and robustness of hepatitis disease classification. By integrating multiple machine learning models—including tree-based learners, boosting algorithms, and meta-level stacking—the proposed approach effectively captured complex, nonlinear patterns within clinical and biochemical data. The hybrid ensemble demonstrated superior performance compared to individual classifiers by reducing variance, minimizing bias, and improving generalization capability across diverse patient profiles. Experimental results confirmed that the hybrid ensemble achieved higher accuracy, sensitivity, specificity, and F1-score, making it a strong candidate for clinical decision-support systems. The ability of the framework to detect subtle patterns in hepatitis-related features ensures early and more precise diagnosis, which is critical for improving patient outcomes and reducing disease progression. Overall, the proposed hybrid ensemble framework provides a reliable, scalable, and interpretable solution for hepatitis disease classification. Future work may include incorporating deep learning architectures, expanding the dataset with multi-center clinical records, and deploying real-time predictive tools for healthcare practitioners. With further refinement, the framework holds strong potential for integration into intelligent healthcare systems aimed at improving diagnostic efficiency and patient care.

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