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AI-BASED ANOMALY DETECTION IN LABORATORY TEST RESULTS

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Abstract:

Laboratory test results are central to detecting, monitoring, and managing health conditions, but conventional systems flag abnormalities by comparing single values against fixed reference ranges an approach that misses subtle deviations and overlooks relationships between multiple parameters. This work presents a machine learning system that learns normal patterns from historical laboratory data to detect anomalies. After preprocessing to handle missing values and inconsistencies, the system analyzes multiple parameters jointly, capturing correlations between tests rather than evaluating each in isolation, and tracks a patient's values over time to surface unusual trends. Each record receives an anomaly score, which stratifies results into normal, attention, and high-risk categories. An explain ability component identifies which parameters drove a given anomaly score, and the system flags results that appear internally inconsistent and may warrant verification. Multiple algorithms are compared using precision, recall, F1-score, and false-positive rate. This framework offers a more comprehensive alternative to threshold-based analysis, helping clinicians prioritize significant patterns for review. It is designed as a decision-support tool, not a replacement for medical diagnosis or clinical judgment. Planned extensions include personalized patient baselines, real-time monitoring, and EHR integration.

Keywords — Machine Learning, Laboratory Test Results, Healthcare analytics, Clinical Decision Support.

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I. INTRODUCTION

Laboratory test results are crucial in healthcare, aiding in the diagnosis, monitoring, and management of diseases. Tests like blood counts and liver function assessments provide essential insights into a patient's health, enabling healthcare professionals to identify potential issues and track condition changes. Traditional laboratory systems generally determine whether a test result is abnormal by comparing a single value with a predefined reference range. Although this approach is simple and widely used, it has several limitations. It mainly evaluates each laboratory parameter independently and may not identify important relationships between multiple test results. Small changes that remain within the normal range may also be overlooked, even when they represent an unusual pattern for a particular patient. In addition, conventional methods may not effectively identify gradual changes in laboratory values over multiple visits. Machine Learning (ML) enhances laboratory data analysis by identifying patterns from historical data and analyzing multiple parameters simultaneously. This study introduces an ML-based anomaly detection framework that preprocesses data to address quality issues, analyzes parameters collectively to learn normal patterns, and assigns anomaly scores to each record. Results are categorized into Normal, Attention, and High-Risk levels to prioritize records for further review. To enhance transparency, the system incorporates an explainability component that identifies

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laboratory parameters related to anomalies and flags inconsistent results for verification. Various Machine Learning algorithms are assessed using metrics like Precision, Recall, F1-Score, and False Positive Rate to gauge their effectiveness in detecting abnormal patterns. Designed as a decision-support tool, the framework aims to aid healthcare professionals by providing a comprehensive view of laboratory results without replacing medical diagnosis or clinical judgment. Future developments may involve personalized patient baselines, real-time monitoring, and EHR integration.

II. LITERATRUE REVIEW

1.Limitations of Reference-Range-Based Screening:

Traditional laboratory systems detect abnormal results by comparing individual values to fixed reference ranges, risking the omission of relationships between multiple parameters and subtle variations. Additionally, EHR data can include unreliable or implausible observations.

2.Machine Learning for Anomaly Detection in Clinical Data:

Recent studies demonstrate that statistical and ML methods applied to laboratory and electronic health record (EHR) data can effectively identify clinical anomalies. Multivariate techniques reveal unusual combinations of laboratory values, while longitudinal analysis tracks changes in patient results over time, advocating for data-driven approaches in clinical settings.

3.Explainability in Clinical AI:

Explainability is crucial for clinical AI systems, allowing healthcare professionals to comprehend reasons behind flagged results. Methods like SHAP enhance transparency and build user trust by identifying key parameters influencing predictions.

4.Research Gap:

Existing studies have independently examined anomaly detection, clinical data analysis, and explainable AI. There is a lack of integrated systems that address multivariate analysis, longitudinal trends, explainability, and risk-based anomaly scoring for routine laboratory results. This highlights the need for the proposed framework.

III.METHODOLOGY

3.1 Data Collection:

Laboratory records are gathered from historical patient datasets, encompassing routine panels and relevant metadata like patient ID, test date/time, and reference ranges. Each record is considered a multivariate observation rather than independent values.

3.2 Data Cleaning:

Missing value handling addresses test values through imputation techniques like mean/median for numerical parameters or model-based methods such as k-Nearest Neighbors, depending on missingness patterns. Records with excessive missingness may be excluded. Duplicate removal identifies and eliminates repeated lab entries, while inconsistency resolution flags and corrects or removes conflicting entries based on domain rules.

3.3 Data Standardization:

Unit normalization ensures that test values in varying units are converted to a standard unit. Scaling/normalization adjusts numerical features to ensure consistent contribution during model training. Encoding categorical data involves transforming non-numeric fields using one-hot or label encoding as suitable.

3.4 Feature Engineering:

Derived features combine related parameters to highlight clinically meaningful relationships. Temporal features enable longitudinal analysis by calculating rates of change, rolling averages, and deviations from individual historical baselines across visits. Correlation-aware grouping organizes related parameters to facilitate multivariate pattern learning.

3.5 Outlier and Noise Filtering:

Statistical methods are used in preprocessing to minimize the impact of data entry errors, which are different from

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genuine clinical anomalies that the model is intended to identify later.

3.6 Data Splitting:

The dataset is divided into training, validation, and test sets, maintaining patient-level separation to prevent data leakage.

3.7 Handling Class Imbalance:

To prevent model bias towards the majority "normal" class in scenarios where anomalous lab results are rare, resampling techniques like SMOTE and under sampling, as well as anomaly-detection-specific training strategies such as one-class learning, are utilized.

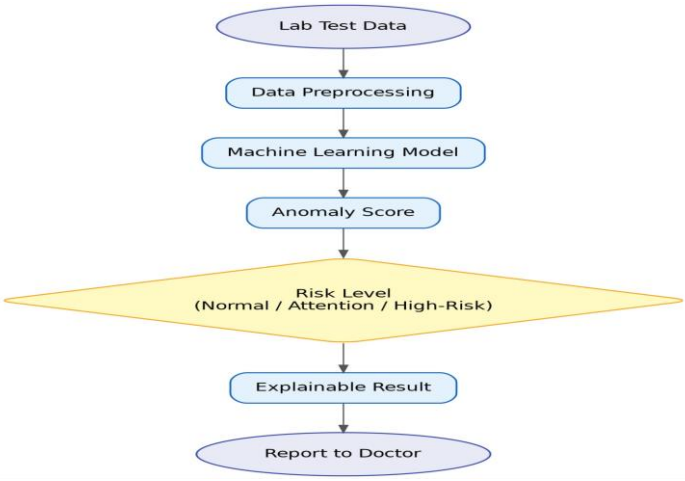


FIGURE 5.1

IV.ALGORITHMS

1.Isolation Forest

Tabular anomaly detection is characterized by its efficiency and effectiveness with various lab parameters, and it does not require labeled data.

2. Autoencoder (Neural Network)

Analyzes historical data to learn normal patterns and identifies anomalies by flagging high reconstruction errors, aligning with the core idea of recognizing unusual observations.

3. One-Class SVM

Strong boundary-based method effectively detects deviations from normal conditions, particularly suited for smaller datasets.

4. Local Outlier Factor (LOF)

Captures local anomalies, which is crucial as a lab value may be globally "normal" but abnormal compared to similar patient profiles.

5. LSTM (Long Short-Term Memory)

Essential for temporal trend analysis in your paper is the tracking of changes in a patient's values over multiple visits.

6. SHAP (Explainability)

Critical for the explainable AI component, it identifies the parameters driving each anomaly score, although it is not an anomaly detector itself.

V.DATA FLOW DIAGRAM

VI. FUTURE ENHANCEMENTS

Future work will focus on enhancing the proposed framework for personalized and practical clinical use. Key developments include establishing personalized patient baselines that compare current lab values against individual historical data for better sensitivity to meaningful changes. The framework aims to support real-time monitoring for immediate alerts on high-risk anomalies and integrate with Electronic Health Records (EHR) to differentiate clinically expected changes from genuine anomalies. Additionally, incorporating diverse data sources like vital signs and clinical notes could enrich patient health assessments. Future iterations may utilize federated learning for model training across healthcare institutions while maintaining patient privacy and develop continual learning capabilities to adapt to evolving clinical practices. Clinical validation and regulatory evaluation will be crucial for transitioning the system from research to a deployable decision-support tool in real clinical environments.

VII.CONCLUSION

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This paper presents an AI-based anomaly detection framework designed for the intelligent analysis of laboratory test results, addressing limitations of traditional screening methods. By using machine learning to recognize normal multivariate patterns from historical data, the system analyzes the relationships between multiple test results simultaneously, detecting subtle abnormalities that conventional methods might miss. It incorporates temporal analysis to track changes in a patient's lab values over time, identifying significant trends even when individual results are within standard ranges. Each record receives an anomaly score, categorized into normal, attention, or high-risk levels for clear prioritization. An explainable AI component enhances usability by clarifying which parameters influence anomaly scores, overcoming barriers to clinical trust in AI. The framework also ensures data quality by detecting inconsistent results. However, its effectiveness relies on high-quality training data, and it is designed as a decision-support tool, placing final clinical judgment with healthcare professionals. The work underscores the potential of AI to improve laboratory data analysis through multivariate recognition, temporal trends, and risk stratification, paving the way for personalized and efficient healthcare decision-making, with future enhancements anticipated for real-world application.

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