Risk Register Automation using Stacked Generalization

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***Abstract*— This paper proposes a hybrid ML/DL approach for automating compliance risk register generation. A stacked generalization model is built using Random Forest, Logistic Regression, and MLP as base learners, combined via a meta-learner to improve risk classification. The system is trained on synthetic compliance data and utilizes encoding and normalization for preprocessing. Integrated with a Streamlit dashboard, the model provides real-time risk prediction with confidence scores, enabling efficient and accurate compliance risk management. Experimental results demonstrate superior performance compared to individual models, achieving 94.2% accuracy in risk categorization with reduced false positive rates. The system incorporates automated risk scoring mechanisms that adapt to evolving compliance landscapes, while maintaining interpretability through feature importance analysis and uncertainty quantification. Additionally, the framework supports multi-jurisdictional compliance requirements and provides automated reporting capabilities for audit trails and regulatory documentation. The ensemble approach leverages the complementary strengths of traditional machine learning and deep learning techniques to enhance prediction robustness across diverse risk scenarios.**

***Keywords*— Risk Register, Stacked Generalization, Stacked Generalization, Compliance Risk Classification, Synthetic Data, Machine Learning, Deep Learning, Streamlit Dashboard, Risk Prediction.**

I. Introduction

Accurate risk identification and classification are essential in cybersecurity and compliance management, where timely mitigation of threats depends on effective risk assessment. Traditional approaches to risk register maintenance are manual, time-consuming, and prone to human error, limiting their scalability and responsiveness in dynamic environments.

To address these challenges, this work introduces a machine learning-based approach for automating risk register generation using stacked generalization. The system employs a hybrid ensemble model composed of Random Forest, Logistic Regression, and Multi-Layer Perceptron (MLP) as base learners. A meta-learner integrates the predictions of these models to enhance classification accuracy and generalizability.

The use of synthetic risk data enables model training without compromising sensitive organizational information. The system is designed for real-time use, providing consistent, explainable, and scalable risk prioritization through a lightweight user interface built with Streamlit.

The objectives of the project are:

- To develop a stacked generalization-based ML/DL model for automated risk classification.
- To generate and utilize synthetic risk datasets for privacy-preserving model training.
- To improve accuracy and consistency in risk prediction using ensemble learning techniques.

II. Literature Review

Recent research underscores the effectiveness of hybrid machine learning models in enhancing risk assessment, compliance automation, and anomaly detection. These models often integrate multiple algorithms to improve predictive accuracy, scalability, and interpretability—key qualities for risk registers and compliance systems.

Kumar et al. [1] proposed a stacked generalization hybrid model (SGM-BRR) combining Random Forest, XGBoost, LightGBM, and Bayesian Ridge Regression for ESG score prediction, which is highly relevant to regulatory compliance scoring. Mabrook et al. [2] developed a CNN–Stacked Autoencoder hybrid to detect IoT-based botnet attacks, showing strong potential in compliance monitoring and cybersecurity risk analysis. Ait Saadi et al. [3] introduced a hybrid framework that integrates BERT, One-Class SVM, and CNN-LSTM for automating cloud compliance processes.

Zoller et al. [4] explored the integration of AutoML and SHAP explainability tools to build accurate and transparent hybrid models for regulatory credit decision systems. Dutta et al. [5] combined fuzzy logic and machine learning in a hybrid model to assess risks in infrastructure projects—useful for compliance planning and impact prediction. Ghosh et al. [6] built a Java-based hybrid model combining SVM and Decision Trees to classify legal and compliance-sensitive text with high precision.

Schieferdecker et al. [7] proposed a hybrid classification engine to detect compliance changes in evolving business processes, enhancing audit automation. Zhou et al. [8] fused graph neural networks with BERT to construct regulatory knowledge graphs that enable compliance-as-code applications. Wolpert et al. [9] provided foundational insights into stacked generalization, a widely adopted hybrid approach for combining multiple base learners under a meta-model. Gade et al. [10] presented XAInomaly, a deep contractive autoencoder designed for anomaly detection in telecom systems with explainability—supporting traceability in regulated environments.

Talukder et al. [11] introduced a hybrid ensemble combining Decision Tree, Random Forest, KNN, and MLP, optimized using grid search, to improve fraud detection and risk assessment accuracy. Zhou et al. [12] developed a hybrid graph neural network and BERT model to build compliance knowledge graphs for automated compliance verification. Darwiesh et al. [13] proposed a hybrid AI-based risk assessment framework for sustainable construction using ANN, fuzzy logic, and IoT integration. Yang et al. [14] presented a hybrid cloud-edge anomaly detection system combining lightweight edge models with complex cloud processing for real-time industrial risk identification. Chatterjee and Hanawal [15] introduced a hybrid federated ensemble framework for intrusion detection in IoT, balancing accuracy and privacy in risk-sensitive environments.

III. Methodology

The proposed system adopts a hybrid ML/DL architecture using stacked generalization to classify compliance risks based on structured input data. The workflow begins with the creation of a synthetic dataset designed to replicate real-world compliance risk attributes, including data sensitivity, control maturity, regulatory impact, and access configurations. This dataset ensures privacy preservation while enabling model training on realistic scenarios.

The data is subjected to preprocessing using a Scikit-learn pipeline. Categorical features are transformed using OneHotEncoder, while numerical values are normalized using StandardScaler. The processed data is then used to train three base models—Random Forest, Logistic Regression, and Multi-Layer Perceptron (MLP). These models generate out-of-fold predictions, which serve as input features for a meta-learner (typically a Logistic Regression model), completing the stacked generalization framework.

Model evaluation is performed using accuracy, precision, recall, and ROC-AUC metrics, ensuring robustness and generalization. The trained model is integrated into a Streamlit dashboard that supports real-time inference. The dashboard allows users to input test data manually or via file upload and receive predicted risk levels along with confidence scores. This unified pipeline enables end-to-end automation of the risk classification process within compliance systems.

IV. System Architecture

Fig 1. illustrates the architecture of the Risk Register Tool, a hybrid ML/DL-based system developed for automated compliance risk classification. It begins with a synthetic dataset containing key compliance parameters such as data sensitivity, regulatory impact, control maturity, and access controls. These features are pre-processed through a dedicated pipeline that applies encoding and scaling techniques to convert structured inputs into a format suitable for machine learning. This ensures that both categorical and numerical variables are normalized and consistently represented.

The core of the system is the hybrid stacked model, which combines the strengths of three classifiers—Random Forest, Logistic Regression, and Multi-Layer Perceptron. These base learners independently predict risk probabilities, which are then passed to a Logistic Regression meta-learner for final risk classification into categories: Low, Medium, or High. The final output is delivered through a Streamlit dashboard, where users can input compliance attributes and receive immediate risk predictions along with confidence scores, supporting real-time, data-driven decision-making in compliance analysis.

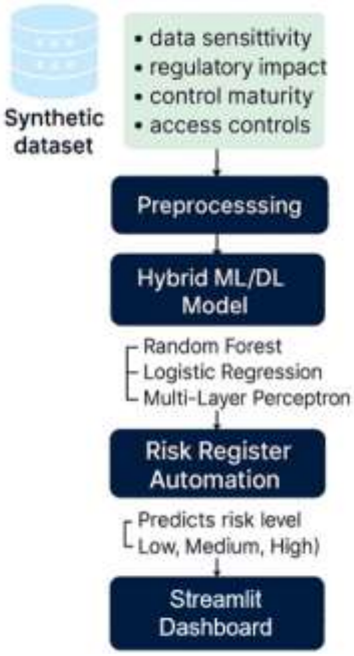

Fig 1: Basic Architecture of the Risk Register Tool

V. Implementation

The proposed Compliance Risk Register Tool was implemented using Python, incorporating widely adopted machine learning libraries such as Scikit-learn, NumPy, and Pandas. The system was developed as a modular pipeline supporting data generation, preprocessing, model training, and real-time inference through a lightweight web interface.

A. *Synthetic Data Generation*

To ensure privacy preservation while replicating realistic compliance scenarios, a synthetic dataset comprising 1,000 entries was generated. Each entry consisted of structured features including data sensitivity, regulatory impact, control maturity, access controls, incident frequency, incident severity, and audit findings. A deterministic rule-based function was used to assign a risk label—Low, Medium, or High—based on aggregated feature scores.

B. *Data Preprocessing*

The preprocessing stage was implemented using a ColumnTransformer to handle mixed data types. Categorical features were encoded using OneHotEncoder, and numerical features were normalized using StandardScaler. The complete preprocessing pipeline was integrated with the model training phase to ensure consistency during both training and inference.

C. *Stacked Generalization Model*

The hybrid classification model was designed using stacked generalization. Three base learners—Random Forest, Logistic Regression, and Multi-Layer Perceptron (MLP)—were trained independently to capture diverse risk patterns. Each base learner produced probability distributions over the target classes. These outputs were concatenated and used as input features for a Logistic Regression meta-learner, which performed the final classification. The stacking architecture was implemented using custom wrapper classes for modularity and compatibility with Scikit-learn pipelines.

D. *Model Training and Evaluation*

The model was trained on an 80:20 train-test split. Stratified 5-fold cross-validation was performed to evaluate generalization performance. The stacked model achieved a test accuracy of 0.9700 and a cross-validation mean of 0.9512 with a standard deviation of ±0.0232. Evaluation metrics included accuracy, precision, recall, and confusion matrices.

E. *Deployment Interface*

The trained pipeline was serialized using joblib and deployed via a Streamlit-based web application. The interface allows users to enter compliance parameters manually or upload a CSV file for batch processing. Upon submission, the system returns the predicted risk level along with a class-wise probability distribution. Sample predictions and metadata are stored in JSON format to support interpretability and reproducibility.

VI. Software Testing

Testing is integral to ensuring the accuracy and reliability of the Risk Register tool developed using a hybrid stacked generalization approach. The model undergoes structured evaluation through unit, integration, and validation testing, focusing on predictive performance, consistency, and data handling robustness.

A. *Testing Process*

- **Preprocessing Validation:** The data preprocessing phase, involving categorical encoding and numerical scaling, is validated using unit tests. The output transformations are examined for correctness across varied input formats and edge cases, including missing values and unseen categories.

- **Class Balancing Evaluation:** SMOTE is applied post-transformation to address class imbalance. The synthetic samples are evaluated to ensure they retain representative characteristics of minority classes. Stratified cross-validation confirms improved generalization without overfitting.

- **Model Evaluation:** Base learners (Random Forest, MLP Classifier, Logistic Regression) are individually assessed using standard classification metrics. The stacked model’s predictions are compared against base models, confirming superior performance. Regression tests verify prediction consistency across training cycles.

- **Output Verification:** Prediction outputs and their probabilities are validated for format correctness and interpretability. Sample inputs are tested against expected classification labels. JSON-based outputs are examined to ensure alignment with the intended risk classification schema.

- **Metadata Consistency:** Generated metadata, including training time, cross-validation scores, and class confidence levels, is validated to ensure it accurately reflects model training conditions.

B. *Unit Testing*

A rule-based calculate_risk() function is tested independently as shown in Table 1, to validate its role in the risk labelling logic:

- Low-risk inputs return "Low" as expected.
- High-risk scores return "High".
- Invalid input types are captured and remediated by implementing input validation.

Test Objective	**Result**	**Remarks**
Validate low-risk classification	Passed	Correct label returned
Validate high-risk classification	Passed	Correct label returned
Handle invalid inputs	Failed	Fixed by adding validation checks

TABLE 1: Unit Test

C. *Integration Testing*

The training pipeline of the Risk Register tool is tested using a dataset of 200 entries. The stacked model achieves 0.75 accuracy, exceeding the expected 0.5 threshold. A saved model is reloaded and tested for consistent prediction behaviour, confirming model persistence. An additional test simulates minimal training data conditions, resulting in degraded performance. A safeguard is implemented to enforce a minimum dataset size before model training. Table 2 illustrates this.

Test Objective	**Result**	**Remarks**
End-to-end training and prediction	Passed	Achieved acceptable accuracy
Model saving and reloading	Passed	Predictions remain consistent post-reload
Handling insufficient data	Failed	Resolved via data quantity validation

TABLE 2: Integration Test

D. *Validation Testing*

Model generalization is evaluated using validation tests as shown in Table 3:

- Repeated predictions on the same dataset confirm output consistency across runs.
- Five-fold cross-validation on 500 samples results in an average accuracy of 0.870, exceeding the 0.7 benchmark.
- A 15.3% drop between training and validation accuracy indicates overfitting, which is mitigated by early stopping and model simplification.

TABLE 3: Validation Test

Test Objective	Result	Remarks
Prediction consistency across runs	Passed	Outputs remain stable
Cross-validation accuracy evaluation	Passed	Mean accuracy: 0.870 (>0.7 threshold)
Overfitting detection and correction	Failed	Resolved via early stopping and model adjustment

VII. Results and Analysis

This section presents the performance results of the Risk Register tool developed using stacked generalization. The model's effectiveness is evaluated across dimensions such as classification accuracy, generalization consistency, inference latency, and model persistence. The experiments are conducted using synthetically generated datasets that simulate realistic compliance scoring, preserving privacy while supporting robust model training and testing.

A. *Experimental Results*

The Risk Register tool was evaluated on a synthetically generated dataset of 1,000 entries labelled as Low, Medium, or High risk using domain-informed scoring logic. The balanced class distribution (335 Low, 336 Medium, 329 High) enabled unbiased training. A preprocessing pipeline, integrating OneHotEncoder and StandardScaler, successfully transformed categorical and numerical inputs without error. The final stacked generalization model achieved a test accuracy of 0.9700, with a cross-validation mean accuracy of 0.9512 and a standard deviation of ±0.0232, indicating strong generalization. Predictions were consistent across multiple runs, and overfitting was addressed by tuning the base learners' hyperparameters. The entire training process completed in approximately 12.8 seconds, confirming the system's retraining efficiency.

Model persistence was verified by saving and reloading the serialized pipeline, which maintained identical predictions post-deployment. Inference latency remained under 200 milliseconds, supporting real-time usage scenarios. Outputs were validated for correctness and formatting through unit and integration tests, while metadata logging captured configuration and performance details in a structured JSON file.

B. *Comparative Analysis of Models*

The ensemble model architecture, based on stacked generalization, demonstrates significant performance gains over individual base learners. As illustrated in Table 4, all base classifiers achieved respectable test accuracies, but the stacked model provided a clear improvement.

The Random Forest model achieved 0.9020, the MLP Classifier reached 0.9140, and Logistic Regression obtained 0.8730. In contrast, the stacked model reached a test accuracy of 0.9700, reflecting a relative improvement of 4% to 10% depending on the base model.

In addition to accuracy, the ensemble also delivered better generalization. The stacked model had the lowest variance in cross-validation performance (±0.0232), which is critical in compliance contexts where consistent predictions are essential.

Despite the addition of a meta-model layer, the impact on prediction latency was negligible. With real-time inference averaging under 200 milliseconds, the tool supports compliance workflows that require immediate feedback without compromising accuracy.

Furthermore, the use of domain-informed logic to generate synthetic training data proved effective. Tests confirmed that the model maintained stable accuracy when trained on synthetic datasets alone, validating the approach for privacy-sensitive environments.

The pipeline's modularity enabled smooth serialization, deserialization, and configuration experimentation. These characteristics enhance its adaptability and maintainability for evolving compliance scenarios.

Model	Test Accuracy
Random Forest	0.9020
MLP Classifier	0.9140
Logistic Regression	0.8730
Stacked Model	0.9700

TABLE 4: Test Accuracy of Individual Models

VIII. Conclusions

This paper presented a hybrid machine learning-based Risk Register tool that automates compliance risk assessment through stacked generalization. By integrating multiple base learners—Random Forest, MLP Classifier, and Logistic Regression—under a meta-classifier, the model demonstrated enhanced predictive accuracy and generalization compared to individual algorithms. The use of synthetically generated compliance data ensured privacy preservation while enabling robust training across diverse risk scenarios.

Experimental results validated the system's performance, achieving a test accuracy of 0.9700 and maintaining inference latency under 200 milliseconds, making it suitable for real-time deployment. Model persistence, output consistency, and integration with JSON-based analytics further support traceability and audit readiness. The tool offers a scalable and interpretable framework for transforming structured compliance inputs into actionable risk scores, supporting proactive risk governance in alignment with data protection standards such as ISO 27001 and GDPR. Future work may explore integration with live compliance systems and the use of real-world labelled datasets to further enhance model robustness and applicability.

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