



ARTIFICIAL INTELLIGENCE-DRIVEN RISK PROFILING:

STRATEGIC APPROACHES TO ELEVATE THE QUALITY OF INDONESIAN VALUERS

 27^{th} ASEAN VALUERS' ASSOCIATION — BANGKOK, THAILAND



Artificial Intelligence-Driven Risk Profiling: Strategic Approaches to Elevate The Quality of Indonesian Valuers



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Artificial Intelligence-Driven Risk Profiling: Strategic Approaches to Elevate Quality of Indonesian Valuers







RESEARCH INTRODUCTION





Compliance Challenges for Indonesian Valuers

Critical Role of Valuers



Influence asset valuation, financial reporting, taxation, and investment decisions.

Risk from Non-Compliance



Legal, reputational, and financial risks arise from violations, intentional or accidental.

Limitations of Current Oversight



- Traditional compliance is reactive, manual, and resource-intensive.
- Difficult to detect risks before they escalate.

Regulator y Gap



- No validated,
 systematic risk based profiling
 mechanism exists.
- Need for real-time,
 data-driven,
 proactive
 monitoring to focus
 on high-risk
 entities.



Objectives of Al-driven Risk Profiling

Develop Alpowered Risk Profiling



Machine learning model to assess compliance risk of valuers.

Enhance Regulatory Efficiency & Accuracy



Prioritize highrisk entities for targeted supervision. Enable Proactive Compliance Monitoring



Shift from manual, reactive oversight to real-time, data-driven assessment.

Support Policy & Strategy Development:



Provide actionable insights for regulators (DPPPK) to design more systematic compliance strategies.



Analytics Model

8.

RESEARCH INTRODUCTION

Model-Based (fixed rule based)

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System-Based (based on dynamic data & intelligence)

Problem Statement & Objectives

No.	ASPECT	EXSISTING CONDITION	PROPOSITION	
1.	List of Risk Targets	Only produced at the beginning of the year	Regular updates per semester	
2.	Risk Profile	Cyclical, not updated in the current year	Continuous Workflow, multi-source based and regularly updated	
3.	Committee Role	The Sanctions Committee is limited to imposing sanctions	Comprehensive Compliance Committee, involved from end to end processes	
4.	Supervisory Governance	Governance supervision is not optimal	More accountable governance oversight	
5.	Compliance Standards	Not yet formulated explicitly and clearly	Compliance standards are formulated more clearly and transparently	
6.	Team Collaboration	Limited to structural positions	Inclusive – involving all work groups	
7.	Efficient Allocation of Human Resources and Time	Less than optimal because the implementation of supervision is not hierarchical	More efficient – implementation of tiered supervision based on more comprehensive risk profiling	





LITERATURE REVIEW

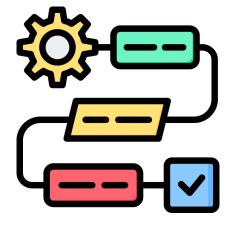






Authors (Year)	Region / Sector Focus	Period / Scope	Key Findings	Relevance to Current Study
Giudici, Centurelli & Turchetta (2024)	Europe – Financial Professions	Conceptual Framework	Introduced the use of AI and ML in compliance risk profiling for financial professions.	Provides foundational framework for AI-based compliance monitoring at DPPPK.
Feng, Liu & Yuan (2025)	China – Financial Regulation	Empirical (2020–2024)	Demonstrated the predictive accuracy of LightGBM in identifying compliance violations using limited datasets.	Supports the methodological choice of LightGBM for Indonesian valuers' risk profiling.
Heß & Damásio (2025)	EU – Financial Oversight	Policy Study	Advocated for data-driven compliance frameworks over manual audit systems.	Justifies the shift from reactive to proactive monitoring in Indonesia's compliance strategy.
Zhang et al. (2020)	Global – Financial Services	Review Study	Found that ML improves objectivity and reduces bias in compliance risk detection.	Strengthens argument for Al adoption to enhance fairness in Indonesian regulatory processes.
Pattnaik, Ray & Raman (2024)	India – Regulatory Risk Profiling	Case Analysis	Highlighted limitations of traditional, judgment-based risk profiling methods.	Emphasizes the need for automated, data-driven compliance assessment.
Reddy (2025)	Banking & Insurance (AML/Fraud)	Empirical	Showed success of AI in detecting anomalies and early risk patterns.	Provides benchmark for real-time Al-based compliance monitoring.
Fuster et al. (2019)	Financial Valuation Sector	Global	Identified the potential of AI-driven analytics in valuation risk management.	Directly relevant to AI-based compliance in Indonesian valuation profession.





RESEARCH METHODOLOGY

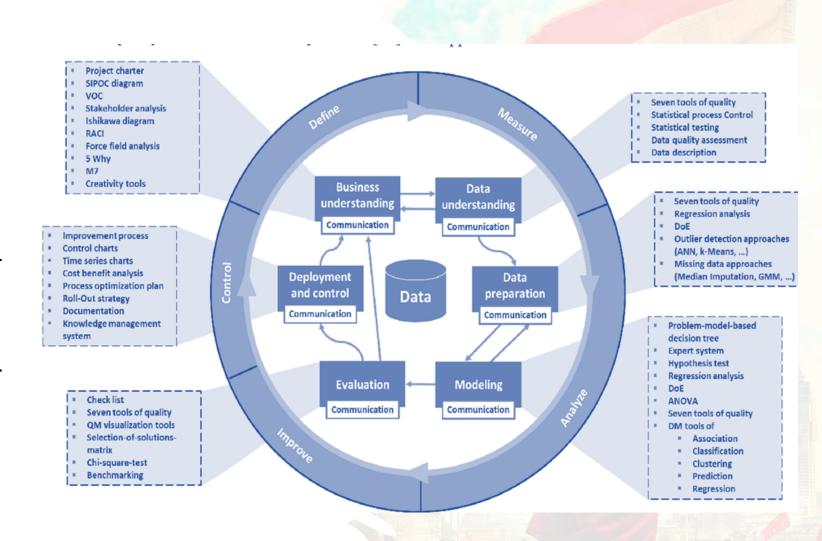




✓ Data-Centric Lifecycle: Ensures continuity and systematic analysis across all stages.

✓ Phases:

- 1. Business Understanding: Define compliance goals & regulatory priorities.
- 2. Data Understanding: Collect and explore historical compliance & risk factors.
- 3. Data Preparation: Clean, preprocess, and engineer features.
- 4. Modeling: Train supervised ML models to predict risk probabilities.
- 5. Evaluation: Assess model performance (accuracy, AUC, SHAP).
- 6. Deployment & Control: Integrate risk scores into compliance monitoring and continuous improvement.
- √ Key Advantage: Continuous risk profiling supports Compliance Improvement Procedure, enhancing strategy efficiency.



RESEARCH METHODOLOGY

AI-Driven Risk Profiling Framework



Concept



Objective

Enable proactive,

data-driven

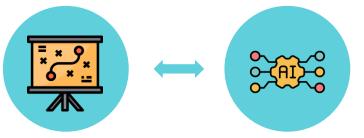
compliance

monitoring for

Indonesian valuers

- Ob**Behefits**isk assessment based on statistical models.
- Early identification of high-risk professionals or firms.
- Supports preventive actions by regulators before violations occur.

Modelling



Approach Use machine learning algorithms to analyze historical data and identify patterns of noncompliance.

Algorithms Used

We compare 15
classification
as a supervisedbased algorithms
to seek the best
for predicting
risk



RESEARCH METHODOLOGY

Data, Variables, and Model Development

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- ✓ We used the data Data & Variables historical data, includes risk factors such as transaction types, previous sanctions, and performance data of valuers
- ✓ A supervised machine learning model was developed to classify valuers based on their risk of non-compliance. The target variable for the model is whether a valuer has been subject to sanctions, while the input variables include transaction types, firm size, and historical compliance data. The model is trained on historical data to detect patterns and predict the likelihood of non-

compliance based on past behaviors
OPERATIONAL

FIRMS

PROFESSION

Total of Valuers	Age of Valuer	Fees per Assignment	Out of Scope Objects
Total of Partners	Working Hours	Backdate Reports	Out of Area Assignments
Total of Branches	Total of Assignments	Anomaly of Total Reports	Type of Reports (Long/Short)
Total of Income	CPD	Total of Object Values	
Missing Report			

Missing Report

Purposes

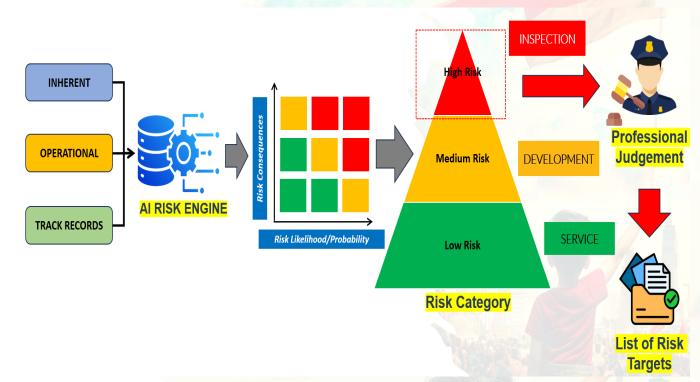
TRACK RECORDS

HISTORY OF SANCTION

Object Ownership Type of Object 1 : sanctioned 0 : not sanctioned

Valuation Business Fields

Model Development



The risk profiling framework used in this study adopts a three-component approach based on ISO 31000 standards for risk management:

- 1. Inherent Risk: Refers to the risks associated with the profession itself, such as the complexity of valuation services.
- 2. Operational Risk: Includes transactional risks associated with the activities carried out by valuers.
- 3. Historical Risk: Pertains to the past compliance behavior of valuers, including their sanction history and adherence to professional standards.



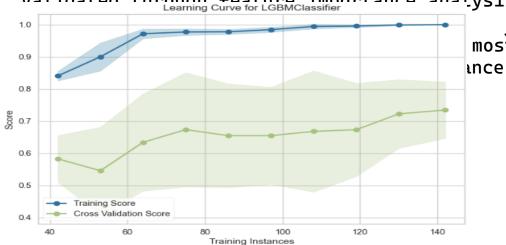


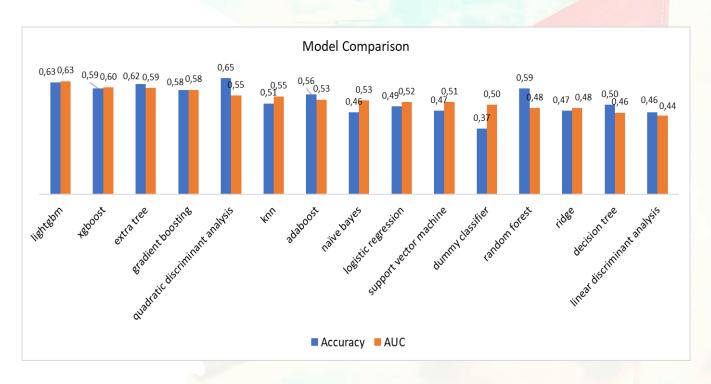




Risk Profiling Model Evaluation

- ✓ Early exploration revealed class imbalance, where the target variable, which is binary historical violation data, was unbalanced. Typically, historical data shows that financial professional entities rarely face sanctions during the inspection phase. Therefore, we decided to use an additional oversampling stage to address this imbalance.
- ✓ We compared several machine learning models to predict risk probabilities, with the best model being LightGBM, which achieved an AUC score of 0.63 and an accuracy of 63%, indicating strong discriminatory power in differentiating between high-risk and low-risk valuers. This performance was further





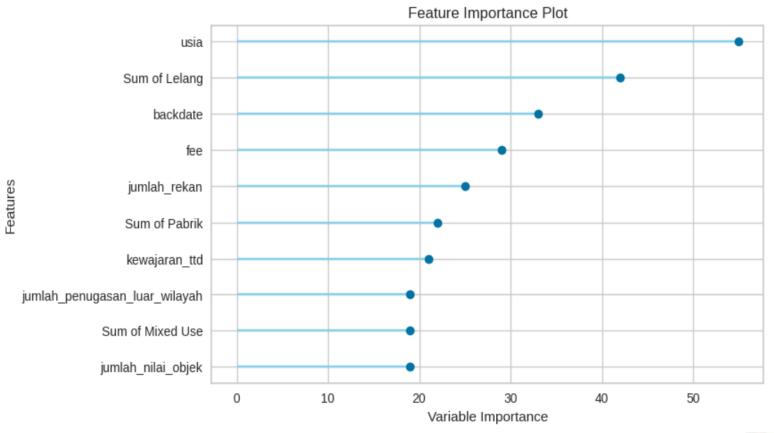
The LightGBM model showed promising potential in early development, as it exhibited a good learning curve (training and cross-validation scores) even with limited training data (as below). We believe that further model development will yield better accuracy results as more training data is collected through field inspections.





Risk Profiling Feature Importance

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✓ Based on this best-performing model, we can also explore the most dominant factors influencing the prediction results (as below). Age and the number of valuations with auction purposes are more dominant compared to other factors in determining the predicted risk outcomes.

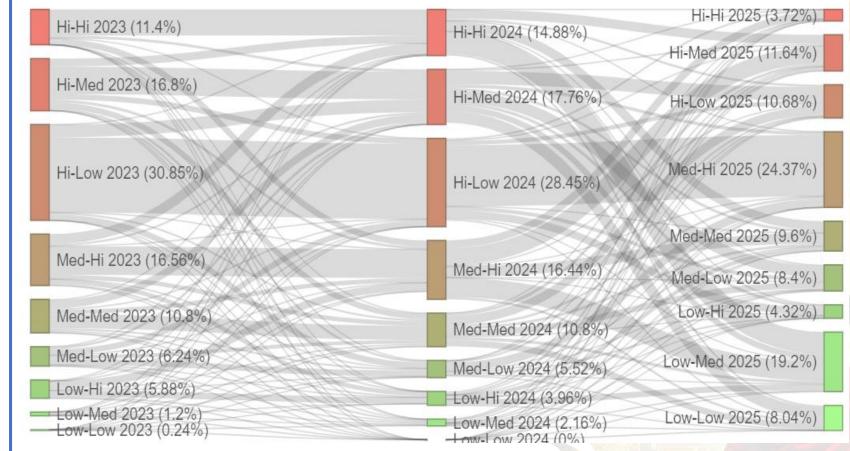




Risk Profiling Trend

Risk Consequence: Total of Object Values





Lower Risk





CONCLUSION









Inamsformation hift in how compliance is managed across the Indonesian valuation profession.

 AI-driven Risk Engine enhances accuracy, efficiency, and proactive monitoring.

Operational

Benefitsidentifies high-risk valuers more
effectively.

- Enables data-driven allocation of regulatory resources.
- Strengthens transparency and accountability in supervision.



Development

- Requires integration of broader data sources and continuous model refinement.
- Future models should reduce reliance on human judgment through improved predictive capability.

Long-term Impact

- Supports sustainable compliance ecosystems.
- Enhances public trust and professional quality among Indonesian valuers.

Al Integration Assessme

Complianc

Efficient Regulation

Profession al Quality



Data Availability & Quality

- Model accuracy is highly dependent on the quantity and quality of historical data.
- Limited datasets (e.g., short time coverage or incomplete records) reduce predictive reliability.
- Expanding data sources from recent years can enhance accuracy and generalization.



Dependence on Professional Judgment

- In cases of data gaps or insufficient history, expert interpretation is still required.
- Machine learning supports decision-making but cannot fully replace human expertise.
- Ongoing collaboration between AI systems and domain experts is essential for trustworthy compliance assessment.

Continuous Learning Process

- Model performance is expected to improve as more data becomes available.
- Requires iterative updates and validation within the compliance monitoring cycle.





FUTURE RESEARCH



Compliance Strategy for Financial Profession

INPUT

Finance Professional Report Data

Finance Professional Service

- · Business activity reports
- · Continuing Professional **Education reports**
- Other service reports

Finance Professional Development

- List of administrative sanctions
- · quality standard procedure assistance list

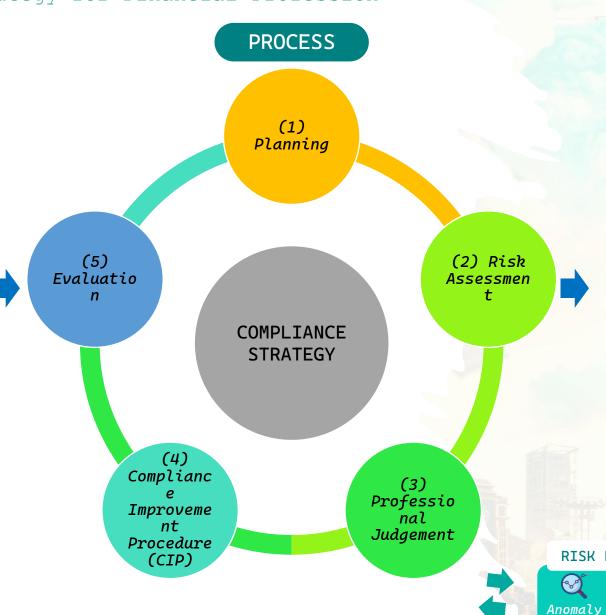
Finance Professional Inspection

- List of inspection results
- List of inspection sanctions

External Data

financial services authority sanctions

association sanctions



OUTPUT

REWARD

SUPERVISION REPORT

TRAINING REPORT DESK REVIEW LETTER OF APPEAL MONITORING RESULT CLARIFICATION REPORT ADMINISTRATION SANCTION

INSPECTION REPORT

DESK REVIEW INSPECTION SANCTION

RISK ENGINE SYSTEM





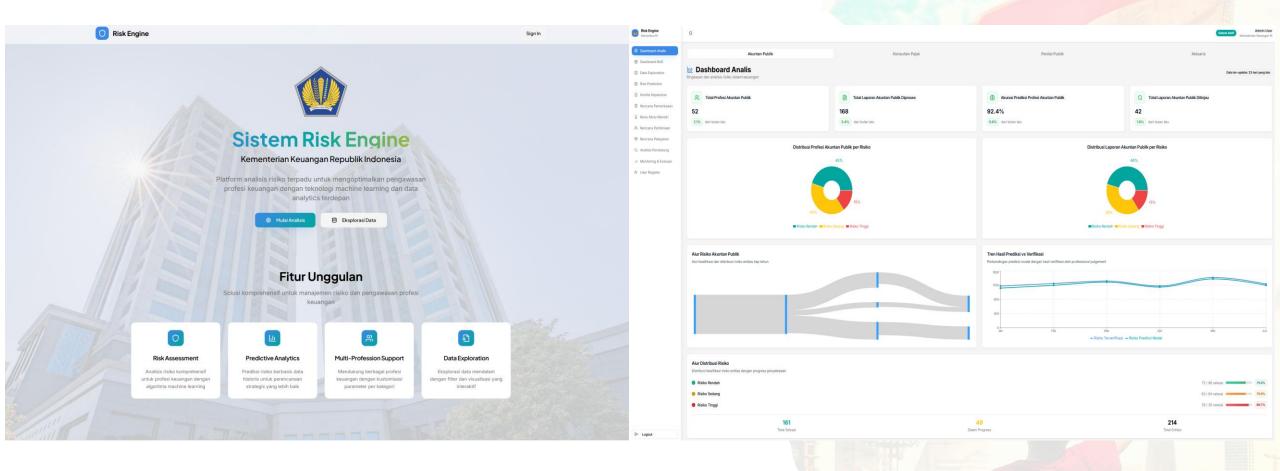


DECISION SUPPORT SYSTEM (DSS)





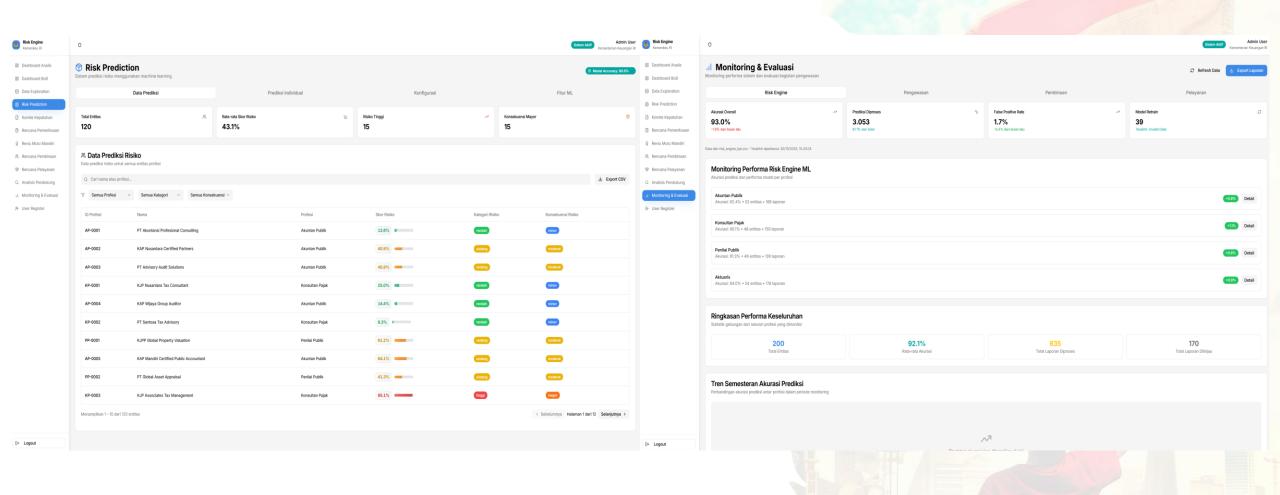






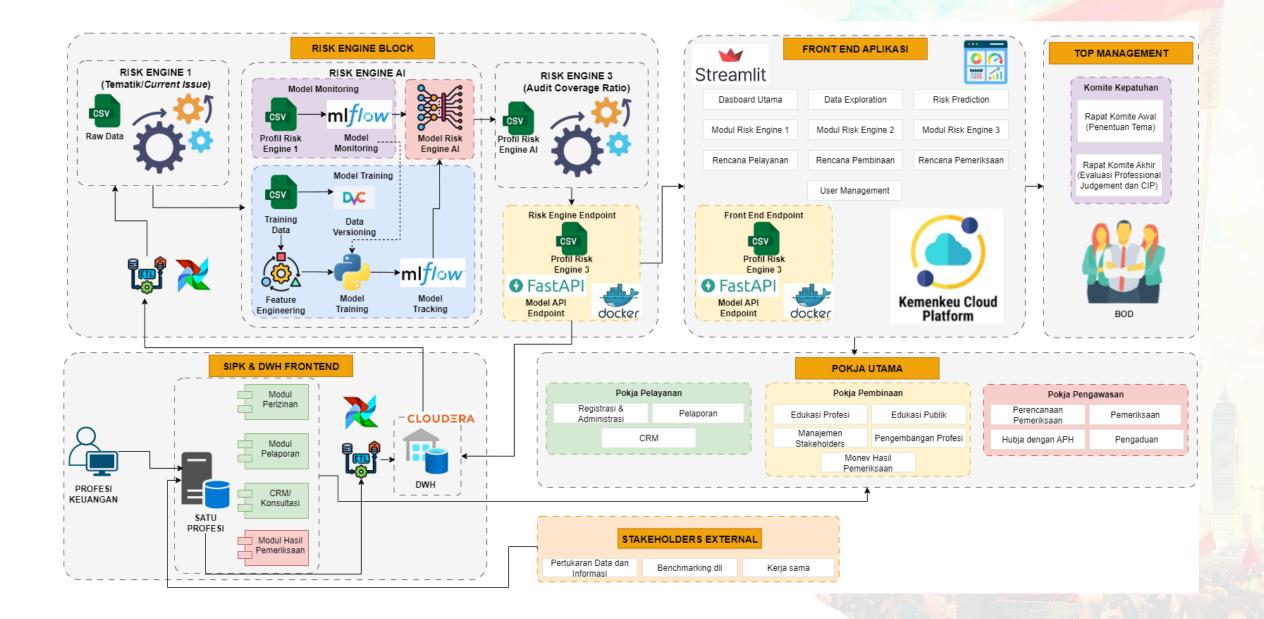
FUTURE RESEARCH Risk Engine Development for Big Data Analytics



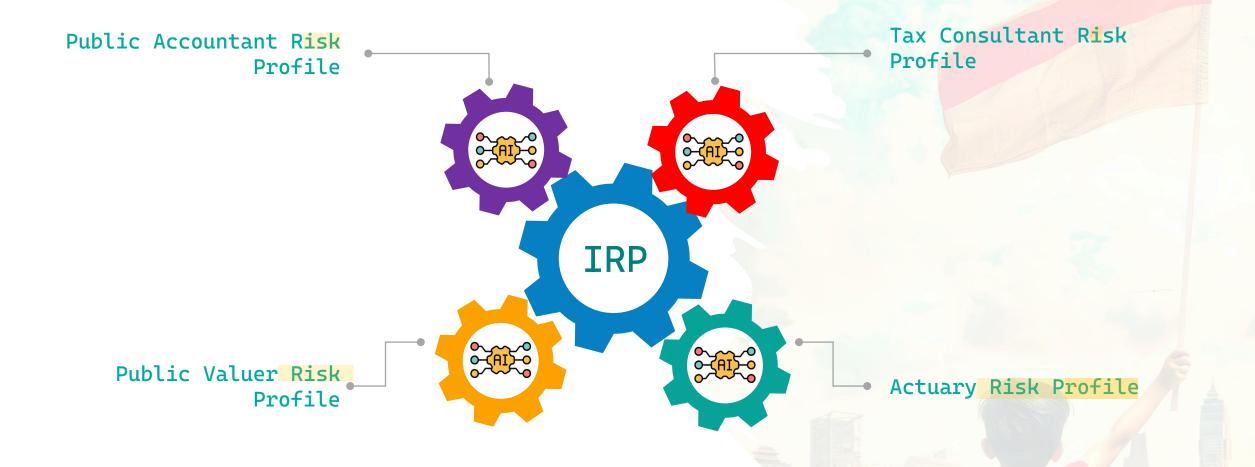




Risk Engine Development for Big Data Analytics













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