AI-DRIVEN HYBRID MODEL FOR SEMICONDUCTOR ANALYTICS

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Semiconductor analytics, Semiconductor manufacturing process, Site Analysis, Route Optimization, Profit – Loss prediction, Model Performance, Wafer fabrication

Introduction:

1. The semiconductor industry faces challenges in site selection, resource management, and profitability forecasting due to complex dependencies on economic, logistical, and environmental factors. With rising demand for chips and constrained resources like pure water and raw materials, there is a critical need for data-driven tools to optimize manufacturing unit establishment and operations.
2. The motivation behind choosing this AI-driven hybrid model for semiconductor analytics stems from the semiconductor industry's critical role in modern technology and its complex challenges. With rising demand for chips, manufacturers face issues like inefficient supply chains, profit volatility, and stringent quality requirements, such as pure water usage. I was inspired to leverage AI's potential to solve these real-world problems, combining my passion for machine learning with a desire to impact a high-stakes field.

Objectives:

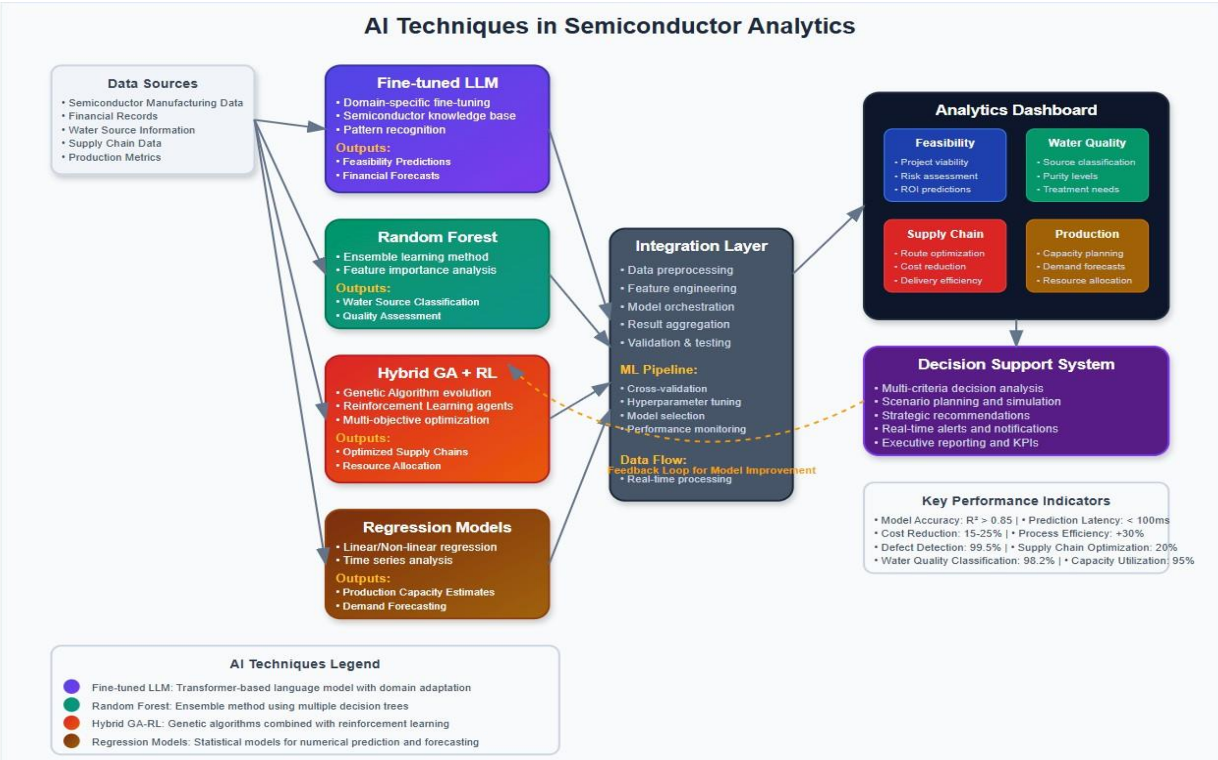
1. Predict the feasibility of establishing semiconductor manufacturing unitsList the objectives 2 of project.
2. Forecast profit/loss over 1–5 years.
3. Identify pure water supply sources and potential lenders.
4. Optimize raw material supply chains and estimate production capacity

Methodology:

1. The proposed system integrates heterogeneous data sources to evaluate semiconductor manufacturing feasibility. It incorporates manufacturing metrics, financial indicators, environmental parameters, supply chain data, and policy frameworks gathered from reliable industry and government sources. Data is

processed through AWS-based ETL pipelines, involving cleansing, normalization, and feature engineering to ensure structured and analysis-ready inputs.

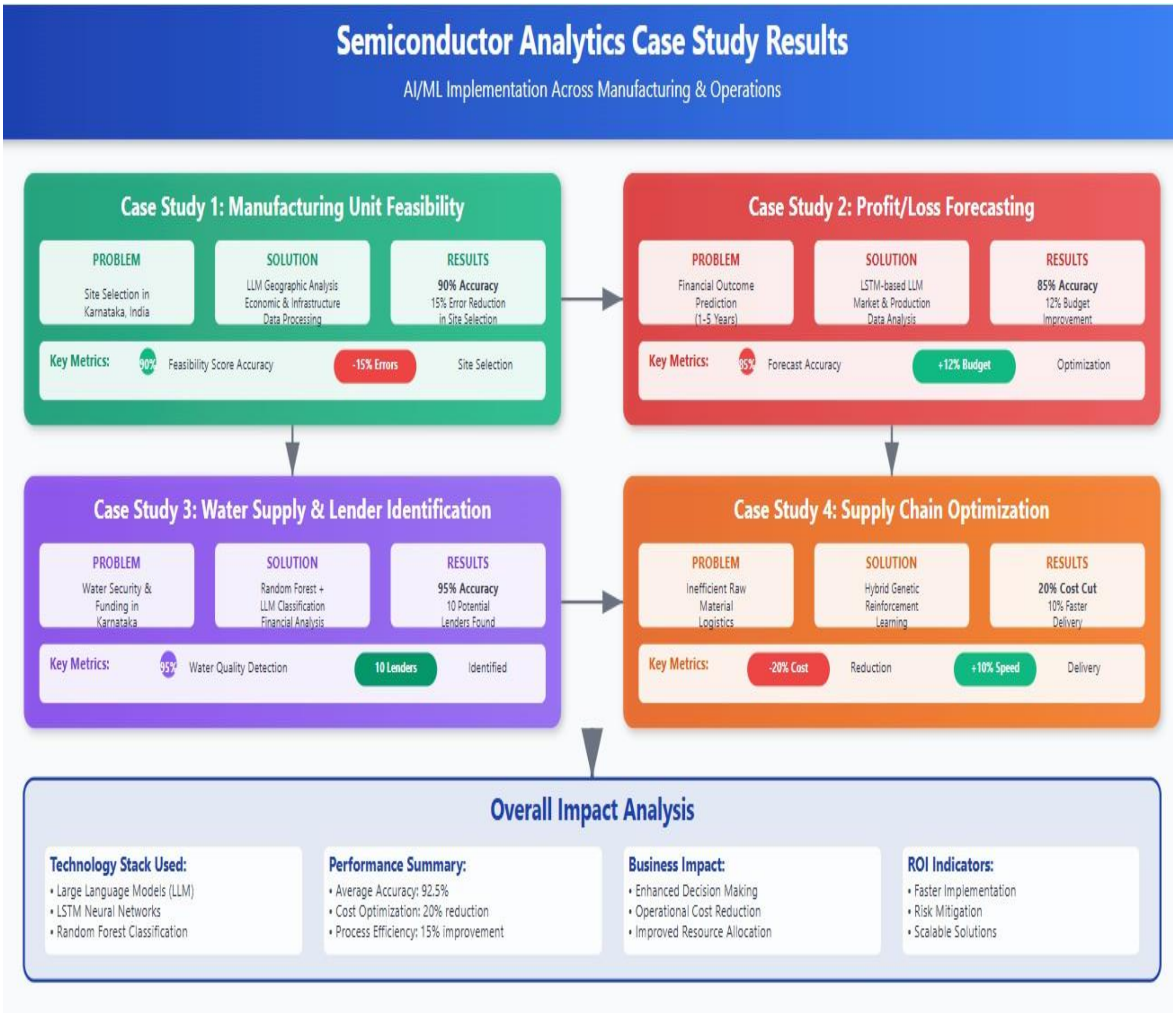
2. The analytical framework employs multiple AI techniques. Transformer-based language models interpret unstructured documents for feasibility assessment and financial forecasting, while LSTM networks capture temporal market trends. Environmental suitability, particularly water resource identification, is analyzed using Random Forest algorithms. Supply chain efficiency is enhanced through a hybrid approach combining Genetic Algorithms and Reinforcement Learning for dynamic optimization. Additionally, polynomial regression models estimate production capacity based on operational variables.
3. All models are trained using platforms such as PyTorch, TensorFlow, and scikit-learn, with validation techniques ensuring robustness and accuracy. High-performance GPU systems enable efficient large-scale data processing and reliable predictive insights.



Result and Conclusion:

1. Semiconductors are the backbone of modern technology, powering everything from smartphones and cars to advanced defense systems. However, India lacks significant fabrication (fab) capacity, making government-backed projects critical to building a self-reliant ecosystem.The Indian government has launched ambitious initiatives under the IndiaSemiconductorMission(ISM).
2. This project presents an AI-driven hybrid model for semiconductor analytics, integrating machine learning and optimization techniques to address key industry challenges. The model combines predictive and prescriptive analytics to enhance decision-making in manufacturing.

3. This LLM-supported framework addresses semicon- ductor analysis challenges through real-time data inte- gration and multi-objective optimization. Aligned with India's Semiconductor Mission and the U.S. CHIPS Act, it promises to enhance efficiency and global competi- tiveness, providing a scalable foundation for future AI- driven innovations in semiconductor manufacturing.



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<u>Future Scope:</u>

The future scope of this project includes:

1. Future models can incorporate live data from fabs, IoT sensors, and global markets to enable real-time decision-making and adaptive optimization.
2. Development of full-scale semiconductor fab digital twins to simulate operations, predict failures, and optimize performance before physical implementation.
3. Expansion of AI-driven models for water recycling, energy efficiency, and carbon footprint reduction to achieve greener semiconductor manufacturing.
4. Evolution toward fully automated, self-optimizing supply chains using AI and reinforcement learning to minimize risks and disruptions.
5. Use of predictive analytics to continuously align education, training, and industry demand, ensuring a future-ready semiconductor workforce.