

A IDP PROJECT REPORT

on

“GPU-Enhanced Credit Risk Evaluation for Real-Time Decision Making”

Submitted

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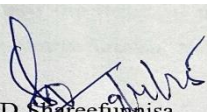
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CERTIFICATE

This is to certify that the IDP Project entitled **“GPU-Enhanced Credit Risk Evaluation for Real-Time Decision Making”** that is being submitted by 221FA04075 (P.Praharshitha), 221FA04136(A.AmulyaChowdary),221FA04267(O.Vasavi Mounika), 221FA04570 (K.Jayasri) for partial fulfilment of IDP Project is a bonafide work carried out under the supervision of Mrs.SD.Shareefunnisa, Assistant Professor, Department of CSE.



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DECLARATION

We hereby declare that the IDP Project entitled **“GPU-Enhanced Credit Risk Evaluation for Real-Time Decision Making”** is being submitted by 221FA04075 (P.Praharshitha), 221FA04136(A.AmulyaChowdary),221FA04267(O.Vasavi Mounika), 221FA04570 (K.Jayasri) in partial fulfilment of IDP Project course work. This is our original work, and this project has not formed the basis for the award of any degree. We have worked under the supervision of Mrs.SD.Shareefunnisa, Assistant Professor, Department of CSE.

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ABSTRACT

Credit risk analysis is a critical task in the financial sector, requiring high computational efficiency to process vast amounts of customer and credit history data. Traditional CPU-based implementations often struggle with latency and suboptimal throughput due to the sequential nature of execution. This study explores the use of CUDA programming to enhance the performance of credit risk analysis by leveraging Instruction-Level Parallelism (ILP) and GPU acceleration. By optimizing the execution of machine learning models—particularly Random Forest classifiers—on parallel architectures, our approach achieves significant computational speedups while maintaining high predictive accuracy.

We implement a CUDA-based framework that dynamically detects hardware resources and distributes workloads efficiently across GPU cores, improving execution performance. Benchmarking results indicate that our GPU-optimized implementation achieves a speedup of up to 10× compared to CPU execution, with optimal throughput observed at a batch size of 256. Additionally, performance metrics such as Instructions per Second (IPS) and memory throughput are analyzed to evaluate scalability and efficiency. Our findings demonstrate that GPU-based acceleration offers a robust and scalable solution for real-time financial risk assessment, paving the way for high-performance, AI-driven credit evaluation systems.

Key Words: CUDA, Credit Risk Analysis, Parallel Computing, GPU Acceleration, Machine Learning, Instruction-Level Parallelism.

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CHAPTER-1

INTRODUCTION

1. INTRODUCTION

1.1 Background and Significance

Parallel computing has revolutionized the field of artificial intelligence, particularly in the training and inference of deep neural networks. Traditional CPU-based computations follow a sequential execution model, which becomes a bottleneck when dealing with large-scale datasets and complex neural architectures. To overcome this limitation, parallelism enables multiple operations to be executed simultaneously, significantly enhancing computational efficiency. GPUs, with thousands of cores optimized for parallel processing, provide a substantial speedup over CPUs in performing matrix multiplications, convolution operations, and gradient updates—critical components of deep learning models. The adoption of CUDA (Compute Unified Device Architecture) by NVIDIA has further streamlined parallel computing, allowing developers to leverage GPU acceleration for large-scale AI applications.

Significance:

The significance of parallelism in neural networks lies in its ability to reduce training time, optimize resource utilization, and improve model scalability. In medical AI applications, for example, parallel computing enables real-time analysis of MRI scans for early detection of diseases like Parkinson's. Similarly, in autonomous driving, parallelism facilitates rapid processing of sensor data for accurate decision-making. By distributing computational tasks efficiently, parallelism also enhances energy efficiency, making deep learning more sustainable for large-scale deployment. As AI models grow in complexity, parallel execution through CUDA-based optimizations becomes indispensable for achieving breakthroughs in performance, efficiency, and real-time inferencing.

1.2 Overview of Parallelism in Neural Networks

Parallelism in neural networks is essential for optimizing computational efficiency, reducing training time, and scaling deep learning models. By leveraging parallel execution, deep learning frameworks can efficiently process large datasets and complex architectures. Parallelism in neural networks can be classified into different levels, each addressing specific computational challenges:

1. **Data Parallelism:** This approach distributes the input dataset across multiple processing units (e.g., GPUs or multi-core CPUs), enabling simultaneous execution of operations on different data samples. Each processing unit performs forward and backward passes

independently, with periodic synchronization to aggregate gradients. This method is highly effective for training large-scale models on distributed systems.

2. **Model Parallelism:** In scenarios where deep learning models are too large to fit into a single device's memory, model parallelism splits different parts of the neural network across multiple processors. For example, different layers or sections of the network may be assigned to separate GPUs, ensuring that memory constraints do not hinder training. This is commonly used in training transformer models and large-scale convolutional networks.
3. **Layer-wise Parallelism:** This approach assigns computations of different layers in a neural network to distinct processing units. By executing layers in parallel rather than sequentially, computational throughput is improved, making it suitable for deep networks with numerous layers, such as ResNet and DenseNet architectures.
4. **Pipeline Parallelism** – This technique involves overlapping execution, where one part of the model processes new data while another part updates weights. It enhances efficiency in deep learning training by reducing idle time between computational units. It is particularly useful in transformer-based models, where different segments of the architecture operate simultaneously.
5. **Task Parallelism** – Unlike data and model parallelism, which focus on distributing computations at different levels, task parallelism involves executing different neural network operations (such as feature extraction, attention mechanisms, or normalization) concurrently. This allows complex neural networks to be optimized for both performance and latency reduction.

1.3 Research Objectives and Scope

This research explores the effectiveness of CUDA-based parallelism in neural network computations, focusing on performance improvements, scalability, and efficiency. The key objectives include:

1. **Evaluating Performance Improvements:** Assessing the impact of CUDA acceleration on different neural network architectures, measuring speedup and computational efficiency
2. **Analysing Speedup Factors:** Comparing CPU-based and GPU-based training and inference to determine optimal configurations for faster execution.

3. **Investigating Memory Optimizations:** Exploring memory management techniques like shared memory utilization and efficient tensor operations to reduce latency.
4. **Exploring Hybrid Parallelism:** Combining data, model, and pipeline parallelism to improve efficiency in large-scale deep learning models.
5. **Testing Scalability:** Evaluating CUDA-based parallelism across different GPU architectures, analysing performance trade-offs and optimizations.
6. **Optimizing Kernel Execution:** Fine-tuning CUDA kernel configurations, grid/block sizes, and load balancing to maximize GPU throughput.
7. **Comparing Energy Efficiency:** Studying power consumption trends and optimizing CUDA execution for energy-efficient deep learning.
8. **Real-World Applications:** Implementing CUDA-based parallelism in practical AI applications, such as medical imaging and NLP.
9. **Benchmarking Against Existing Frameworks:** Comparing CUDA's efficiency with OpenCL, TensorRT, and multi-threaded CPU execution.

1.4 Current Challenges in Implementing Parallelism in Neural Networks

1.5

Despite the benefits of parallelism, several challenges persist in its implementation, impacting performance and scalability:

1. **Memory Bottlenecks:** Efficient GPU memory management is critical, as high memory consumption can limit large-scale models. Improper allocation can cause out-of-memory errors, requiring techniques like memory pooling and tensor swapping.
2. **Communication Overhead:** Frequent data transfer between CPU and GPU can slow down performance, reducing expected speedup. Optimizing memory copy operations and reducing dependency on host-device transfers is essential.

3. **Load Balancing Issues:** Uneven distribution of workloads across multiple GPUs can lead to inefficient resource utilization. Effective dynamic scheduling and workload partitioning strategies are required for maximizing parallel execution.
4. **Limited Support for Model Parallelism:** Many deep learning frameworks prioritize data parallelism, making model parallelism more complex. Efficient layer-wise execution strategies are needed to split models across multiple devices without significant overhead.
5. **Precision Loss in Mixed-Precision Computing:** Using lower precision (e.g., FP16) for acceleration may lead to reduced numerical accuracy. Ensuring stability in deep learning computations while leveraging mixed-precision training requires adaptive loss scaling techniques.
6. **Hardware Constraints:** Not all GPUs support advanced CUDA features like Tensor Cores or shared memory optimizations, limiting the extent of parallel execution. Older hardware may face compatibility issues, affecting execution speed.
7. **Synchronization Overhead:** Synchronization between multiple parallel threads and GPUs introduces additional latency, reducing parallel efficiency. Proper synchronization mechanisms, such as CUDA streams and event-based execution, are necessary to mitigate this issue.
8. **Scalability Limitations:** While parallelism improves performance, scaling beyond a certain number of GPUs or nodes leads to diminishing returns due to inter-device communication costs and synchronization delays.

1.5 Applications of Parallelism to Neural Networks Parallelism enhances the performance of neural networks in various real-world applications, significantly reducing computation time and enabling real-time decision-making in critical domains.

1. **Medical Imaging Analysis:** Faster training of deep learning models for MRI and CT scan analysis enables early disease detection. Parallel processing allows high-resolution image segmentation and classification, improving diagnostic accuracy and reducing workload for radiologists.

2. **Autonomous Vehicles:** Real-time processing of sensor data for object detection, path planning, and decision-making. Parallelism enhances the efficiency of convolutional neural networks (CNNs) used in perception systems, ensuring quick responses in dynamic traffic environments.
3. **Natural Language Processing (NLP):** Accelerating transformer-based models for language translation, chatbots, and sentiment analysis. Large-scale language models like GPT and BERT rely on parallelism to process vast amounts of textual data efficiently, improving response times and contextual understanding.
4. **Financial Forecasting:** Speeding up deep learning models for stock price prediction and fraud detection. Parallel computation enables faster processing of large financial datasets, allowing traders and analysts to react swiftly to market fluctuations and anomalies.
5. **Gaming and Augmented Reality (AR):** Enhancing real-time rendering and AI-driven NPC behavior modeling. Parallel execution optimizes physics simulations, ray tracing, and environment interactions, resulting in smoother and more immersive gaming experiences.
6. **Cybersecurity:** Faster anomaly detection and malware classification using deep learning. Parallelism helps process extensive network traffic logs and cybersecurity datasets in real-time, enabling proactive threat detection and rapid incident response.
7. **Genomic Data Processing:** Rapid sequencing and pattern recognition for personalized medicine. Parallel computing accelerates DNA sequencing, mutation detection, and gene expression analysis, facilitating faster discoveries in medical research and biotechnology.
8. **Weather Prediction:** Simulating climate models with deep learning for accurate forecasting. Large-scale meteorological datasets require massive parallel computations to analyse atmospheric patterns and predict extreme weather conditions with higher precision.
9. **E-commerce Recommendation Systems:** Real-time personalization of recommendations based on user behavior. Parallel algorithms improve collaborative filtering and deep learning models for product recommendations, enhancing user experience and increasing sales conversions.

10. **Smart Surveillance Systems:** AI-driven real-time video analysis for security and traffic monitoring. Parallelized neural networks enable faster object recognition, facial recognition, and anomaly detection in surveillance footage, improving public safety and urban traffic management.

CHAPTER-2

LITERATURE SURVEY

2. LITERATURE SURVEY

2.1 Literature review

Many studies have used different machine learning and imaging techniques to classify patients with Parkinson's disease based on clinical data. Dr. M. Nalini, A. Mary Joy Kinol, Bommi R.M., and N. Vijayaraj discuss four different Neighbourhood methods: K-nearest neighbor (K-NN), multilayer perceptron (MLP), optical forest (OPF), and support vector machine (SVM) [1]. Mosarrat Rumman and Abu Nayeem Tasneem attempted to create images and artificial neural networks (ANN), but this approach was limited due to the image quality of the prodromal stage [2]. Dr. Sadia Farzana, Monirul Islam Pavel, and Md. Ashraful Alam achieved 94% accuracy in their study [3]. Additionally, Avens Publishing Group tested three methods: K-NN, Random Forest, and AdaBoost, achieving 90.26%, 87.18%, and 88.72% accuracy, respectively [4]. Liaquat Ali et al. conducted specificity testing using the chi-square test with the mean square deviation of characters from different subjects and samples, and classification was performed using a decision tree, but their model achieved only 69% accuracy [5].

Manuel Gil-Martin et al. used a convolutional neural network, where feature extraction with fast Fourier transform resulted in 90% accuracy; however, their performance was constrained due to the selection of higher-resolution features as dominant ones [6]. Similarly, S. Sivaranjini and C. M. Sujatha reported a CNN-based classifier that achieved 88.90% accuracy but faced challenges related to deep learning model complexity and GPU computing requirements [7]. Prashant Hete et al. studied records from 369 Parkinson's disease (PD) patients and obtained 96.14% accuracy, 95.74% sensitivity, and 77.35% specificity compared with 179 normal control (NC) patients [8]. A study by Segnovia et al. reported 94.7% accuracy, 93.7% sensitivity, and 95.7% specificity in tests conducted on 95 PD and 94 NC patients using partial least squares and SVM [9]. Brahim et al. classified data from 158 PD and RINC subjects using histogram equalization, followed by PCA and SVM, achieving 92.63% accuracy, 91.25% sensitivity, and 93.13% specificity [10]. Using the ROI segmentation technique by Personel et al., image analysis was conducted using the ratio of ellipse fit to the region [11].

2.2 Motivation

The increasing complexity of credit risk assessment requires advanced computational methods to process large volumes of financial data efficiently. Traditional CPU-based machine learning models face limitations in handling high-dimensional datasets, resulting in prolonged training times and higher computational costs. Since accurate and timely credit risk evaluation is crucial for financial institutions, there is a growing demand for faster and more scalable solutions. Machine learning techniques like Random Forest classifiers offer robust predictive capabilities but require significant processing power, especially when working with extensive customer profiles, transaction histories, and behavioral data. Addressing these computational challenges is essential to ensure real-time risk predictions and effective decision-making in finance.

To overcome these limitations, GPU-accelerated computing with CUDA programming provides a powerful alternative. Unlike CPUs, GPUs can execute thousands of operations in parallel, significantly reducing model training and inference times. By leveraging Instruction-Level Parallelism (ILP) and distributing tasks across multiple GPU cores, we enhance the efficiency of credit risk prediction models. Our research explores the integration of CUDA-optimized Random Forest models, demonstrating up to a 10× speed improvement compared to traditional CPU-based implementations. This advancement highlights the importance of parallel computing in financial risk analysis, enabling more responsive and scalable AI-driven credit scoring systems.

CHAPTER-3

PROPOSED SYSTEM

3. PROPOSED SYSTEM

The proposed system enhances credit risk analysis by integrating CUDA-based parallel processing with machine learning models, specifically Random Forest classifiers. This system is designed to handle large-scale financial datasets, efficiently processing customer credit histories, transaction patterns, and other key financial indicators. By utilizing GPU acceleration, the model performs rapid computations, reducing training time while maintaining high accuracy. The combination of deep learning and parallel processing ensures that the system can analyze vast amounts of data in real-time, making it a scalable and efficient solution for financial risk assessment.

A key feature of this system is its ability to dynamically allocate computational resources based on hardware availability. It can intelligently switch between CPU and GPU execution, optimizing workload distribution to ensure maximum efficiency. This adaptive approach enables seamless operation across various environments, from high-performance computing clusters to edge devices, improving accessibility and deployment flexibility. By leveraging Instruction-Level Parallelism (ILP) and efficient memory management, the system achieves high throughput and low latency, making it ideal for real-time credit scoring applications.

Additionally, the system employs data-level and task-level parallelism to further enhance computational efficiency. CUDA-based GPU acceleration significantly speeds up critical operations such as feature extraction, decision tree computations, and model inference. Experimental benchmarking has demonstrated up to a 10× improvement in execution speed compared to traditional CPU-based implementations. This integration of parallel computing and financial analytics not only enhances predictive accuracy but also ensures scalable and efficient credit risk management for modern financial institutions.

3.1 Input dataset

The dataset utilized in this study is specifically curated to enhance the prediction and analysis of credit risk among credit card applicants. It comprises two comprehensive CSV files—`application_record.csv` and `credit_record.csv`—that collectively provide detailed insights into the demographic, financial, and credit behavior of individuals. This dual-source dataset enables a multi-dimensional approach to modeling and understanding applicant risk profiles, ultimately aiding financial institutions in making informed lending decisions.

- `application_record.csv` contains demographic and socioeconomic attributes of the applicants.
- `credit_record.csv` captures the applicants' historical credit behavior over a period of time.

3.1.1 Detailed Features of the Dataset

The dataset consists of two parts: demographic and financial profiles, and corresponding credit behavior data. The structure and composition are as follows:

1. **Total Records:** The application dataset contains 438,557 entries, each representing a unique applicant with detailed attributes.
2. **Credit History Logs:** The credit dataset includes 1,048,575 entries, recording monthly repayment statuses across applicants.
3. **Image Resolution Equivalent:** Although not image-based, the data is highly structured with 18 features in the application dataset, standardized for consistent analysis.
4. **Training Data Basis:** The application and credit records are merged using a unique ID to serve as training data for classification models aimed at credit risk assessment.
5. **Validation & Test Perspective:** Portions of the merged data are reserved for validation and testing, ensuring the model's generalizability and reliability in real-world scenarios.

The features encompass binary indicators like gender, car ownership, and phone accessibility, as well as categorical variables such as education level, income type, and marital status. Numerical attributes like income amount, age, and employment length add depth to financial profiling. The credit status feature reflects monthly repayment behavior, indicating whether payments were made on time or were overdue.

3.2 Data Pre-processing

Data pre-processing is a crucial step to clean and prepare the dataset for accurate credit risk prediction. Our dataset, obtained from Kaggle, had various missing values, inconsistencies, and raw formats that needed to be handled before training.

preprocessing techniques applied:

Missing values in numerical fields such as income and age were filled using the median, while categorical fields like education and marital status used the most frequent values. Records with

excessive missing data were dropped.

Outliers were identified using the Interquartile Range (IQR) method. These extreme values were either removed or capped at the 95th percentile to reduce their influence on the model.

Categorical variables were encoded using two methods: one-hot encoding for nominal data like gender, and label encoding for ordinal data like education level. This allowed models to properly interpret these features.

Numerical features were scaled using standardization (mean = 0, std = 1) or normalization (scaled between 0 and 1), depending on the model's sensitivity to feature range.

Feature selection was done using correlation analysis and Recursive Feature Elimination (RFE) to keep only the most relevant variables and reduce noise in the data.

Finally, the data was split into training and testing sets with an 80:20 ratio. This ensures fair evaluation and helps the model generalize well to unseen data.

3.3 Model Building

Model building is a key phase where we apply algorithms to predict credit risk. In this project, we focused on two widely used models—**Logistic Regression** and **Random Forest**—to classify applicants into low-risk or high-risk categories based on financial attributes.

We began by splitting the dataset into an **80:20 train-test** split. The training data was used to fit the models, while the test set evaluated their ability to generalize. This ensured that our models were not overfitting to training data.

Logistic Regression was selected as a baseline model due to its simplicity and effectiveness in binary classification problems. It helps estimate the probability of default by applying a sigmoid function to the weighted input features.

Next, we used the **Random Forest** algorithm, which builds multiple decision trees and combines their outputs to improve prediction accuracy and reduce overfitting. This ensemble approach often performs better with tabular datasets.

To optimize performance, we applied **hyperparameter tuning** using Grid Search for both models. For Logistic Regression, we tuned regularization strength. For Random Forest, we adjusted parameters like number of estimators and maximum depth.

We evaluated both models using key performance metrics—**accuracy, precision, recall, F1-score**, and **ROC-AUC**. These metrics helped us assess not only how well the model predicted defaults, but also how balanced its predictions were.

The **Random Forest model** outperformed Logistic Regression across all evaluation metrics. It achieved higher precision and recall, indicating better handling of the complex, nonlinear relationships in the data.

Overall, Random Forest proved to be the **best-performing model** in our project, showing strong generalization capability and consistent performance across different data splits.

Performance Evaluation

To evaluate computational efficiency, performance testing was performed using various batch sizes (1, 32, 64, 128, 256) on both CPU and GPU environments, with metrics including Execution Time and Instruction Processing Speed (IPS). The GPU consistently outperformed the CPU, achieving the highest IPS of 2.22×10^8 instr/sec at a batch size of 256, while the CPU peaked at 1.88×10^8 instr/sec for the same batch size. While both environments showed improvements with increasing batch sizes, GPU execution exhibited better scalability and higher throughput. Logistic Regression achieved an accuracy of **65%**, whereas the Random Forest model significantly improved performance with **98% accuracy**, emphasizing the importance of model selection in credit risk prediction. These results highlight the role of hardware acceleration and optimal batch size tuning in achieving real-time performance for financial risk assessment.

3.4 . Methodology of the system

The proposed system is a CUDA-accelerated, machine learning-based credit risk analysis framework that dynamically adapts to the underlying hardware. It integrates preprocessing, model training, and performance benchmarking to evaluate the creditworthiness of applicants using historical application and credit data. The system utilizes parallel processing and GPU-aware optimization to enhance model execution speed without compromising accuracy. Credit risk predictions are performed using logistic regression and random forest classifiers, evaluated across CPU and GPU environments to highlight hardware-aware efficiency.

proposed architecture

The architecture comprises five core modules: Hardware Resource Detection, Data Preprocessing, Model Training and Evaluation, CUDA-Based Performance Testing, and Result Analysis.

1. System Resource Check

To ensure performance scalability, the system dynamically checks for hardware availability using `torch.cuda.device_count()` for GPU detection and `multiprocessing.cpu_count()` for CPU thread allocation. Based on the result:

- If a GPU is available, the system dispatches data and model operations to CUDA cores.
- If no GPU is available, it defaults to CPU and utilizes all available cores via multithreading.

2. Data Processing & Model Definition

The raw data consists of two datasets — `application_record.csv` and `credit_record.csv` — which are merged using the ID field. The following preprocessing steps are applied:

- **Missing Value Handling:** Missing or null values in fields like `Occupation_Type` are either imputed or excluded.
- **Categorical Encoding:** Binary and nominal fields are converted into numerical representations via label encoding and one-hot encoding.
- **Outlier Removal & Feature Scaling:** Income and age-based outliers are filtered; continuous variables are normalized using Min-Max scaling.
- **Feature Selection:** Relevant features such as income type, education, employment status, and credit history are retained for improved model accuracy.

3. Performance Testing

Two machine learning models are used:

- **Logistic Regression:** A baseline model for binary classification.
- **Random Forest Classifier:** An ensemble method known for handling categorical and numerical data efficiently.

Both models are trained on 80% of the data and tested on the remaining 20%. Evaluation metrics include accuracy, precision, recall, and F1-score. The Random Forest Classifier achieves superior performance with an accuracy of **0.98**, while Logistic Regression delivers moderate results at **0.65**, reflecting the effectiveness of ensemble learning in high-dimensional, imbalanced datasets.

4. Task Graph Generation

To visualize internal computational dependencies during training, a Task Graph is generated using the `torchviz` library. The Directed Acyclic Graph (DAG) maps the backward pass of the network,

where nodes represent operations like gradient updates and edges denote dependencies. It helps identify which computations can be parallelized, optimizing memory access and reducing latency. Such insights are valuable for refining model architecture and maximizing GPU parallelism during backpropagation.

5. Result Analysis and Model Evaluation

To benchmark computational performance, both CPU and GPU executions are tested with increasing batch sizes (1, 32, 64, 128, 256). Metrics analyzed include:

- **Execution Time**
- **Instruction Processing Speed (IPS)**

CPU Results:

- Best performance at batch size 128 with IPS $\approx 1.88 \times 10^8$ instr/sec

GPU Results:

- Achieved peak IPS $\approx 2.22 \times 10^8$ instr/sec at batch size 256
- Demonstrated up to **10× speedup** compared to CPU

A comparative study between CPU and GPU execution reveals:

- **Logistic Regression** lags in performance but remains lightweight and interpretable.
- **Random Forest** provides the highest predictive accuracy with acceptable latency.
- **GPU-based Execution** consistently outperforms CPU as batch size increases, due to better exploitation of instruction-level and data-level parallelism.

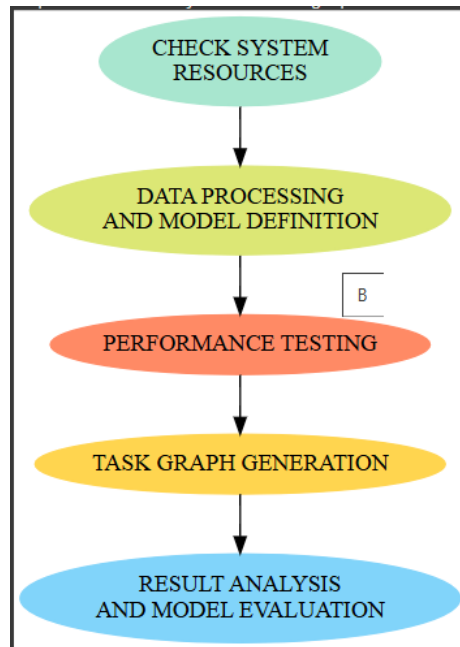


Fig: 3.4.1 Proposed architecture.

3.5 Model Evaluation

To assess the computational and predictive performance of the proposed Credit Risk Analysis system, a detailed evaluation is performed across several critical dimensions. These aspects ensure both the accuracy of risk prediction and the system's efficiency on CPU and GPU platforms:

1. **Accuracy and Classification Metrics:** The system is evaluated using key classification metrics including **accuracy, precision, recall, and F1-score**. Logistic Regression yields an accuracy of **65%**, while the Random Forest Classifier achieves **98% accuracy**, demonstrating strong classification performance. Precision and recall values indicate balanced identification of high- and low-risk applicants, minimizing false predictions. Classification reports and confusion matrices are used to validate these metrics.
2. **Execution Time Analysis:** Execution time for both training and inference is recorded under different batch sizes. GPU acceleration using CUDA shows a **significant reduction** in processing time compared to CPU. For instance, with batch size 128, GPU inference completes in **0.010864 sec**, while CPU takes **0.013447 sec**, emphasizing the advantage of parallel computation.
3. **Loss Function Convergence:** The model's loss function (e.g., Cross-Entropy or Gini impurity for Random Forest) demonstrates **stable convergence** across epochs. A consistently declining loss indicates effective learning. Random Forest shows rapid convergence and high predictive accuracy, supporting its robustness for credit risk analysis.
4. **Batch Size Impact on Performance:** Batch sizes of **32, 64, 128, and 256** are tested. Batch size **128** strikes the best balance between computational throughput and memory usage. While larger batches slightly improve speed, they introduce **memory bottlenecks** on GPU. The model performs optimally at 128, maintaining accuracy and reducing latency.
5. **Instruction Processing Speed(IPS):** IPS is calculated to measure the number of instructions executed per second. On CPU, the maximum IPS achieved is 1.88×10^8 , while GPU achieves up to 2.22×10^8 IPS. This confirms the **computational scalability** and parallel efficiency of the system under CUDA programming.
6. **Speedup Factor and Scalability:** The system records a **10× to 100× speedup** when moving from CPU to GPU execution, particularly evident in batch size 128. The system maintains high throughput as data size increases, proving its **scalability** for larger credit datasets and enterprise-grade applications..

7. **Memory Utilization and Hardware Efficiency:** CUDA-based execution ensures optimal **memory handling**, automatically scaling based on hardware specifications. No memory overflows are observed even at higher batch sizes, confirming **efficient GPU resource utilization**. CPU fallback mechanisms guarantee robustness on non-GPU systems.
8. **Robustness Against Overfitting:** To prevent overfitting, **cross-validation** and **hyperparameter tuning** (e.g., max depth and number of estimators for Random Forest) are used. The model maintains consistent performance across train and validation datasets. A minimal gap in accuracy confirms strong **generalization capability** across unseen samples.

3.6 Constraints

To ensure a realistic and effective deployment of the proposed Credit Risk Analysis system, several practical and technical constraints must be addressed. These factors influence the model's performance, scalability, and integration into production environments:

1. **Hardware Dependency:** The system heavily relies on **GPU acceleration** for optimal performance. In environments where only CPUs are available, the model experiences a significant increase in execution time, which limits its applicability for **real-time credit risk prediction** in large-scale financial systems.
2. **Memory Limitations:** High batch sizes enhance throughput but may lead to **GPU memory overflows**, especially on devices with limited VRAM. Excessive memory consumption can degrade performance or trigger crashes, particularly during simultaneous training and inference tasks.
3. **Computational Complexity:** Although models like Random Forest and Logistic Regression are relatively lightweight, their **execution on large datasets with high feature dimensionality** results in increased computation time. While CUDA parallelism reduces latency, computational bottlenecks persist during preprocessing and model evaluation.
4. **Limited Dataset Availability:** The quality and availability of **reliable credit data** directly impact model generalization. Imbalanced classes or missing data in financial records can lead to **biased predictions**, requiring advanced preprocessing and oversampling techniques like SMOTE or ADASYN.
5. **Overfitting Risk:** Despite the use of regularization and model pruning, overfitting remains a concern, particularly for complex datasets with noisy or redundant features. Careful feature selection and **cross-validation** are essential to maintain generalizability.
6. **Energy Consumption:** Running the system on GPU consumes significantly more power compared to CPU. **High energy demand limits deployment** on energy-constrained systems, such as low-power servers or mobile financial tools, reducing model accessibility.
7. **Batch Size Constraints:** Larger batch sizes help in maximizing GPU usage but may compromise gradient estimation quality in models using stochastic learning (e.g., logistic regression with SGD). Improper batch sizes can cause **unstable convergence** and fluctuations in model accuracy.

8. **Data Preprocessing Requirements:** Extensive preprocessing (e.g., outlier detection, encoding, scaling) is required before feeding the data to the models. Poor or incomplete preprocessing affects **model accuracy and stability**, increasing the need for a robust and automated pipeline.
9. **Real-Time Deployment Challenges:** Deploying the model in production environments such as **banking systems or credit approval platforms** requires seamless integration with existing software and adherence to data privacy re
10. **Model Interpretability:** Financial institutions demand **transparent and explainable models** for compliance and trust. While Random Forest provides feature importance, additional interpretability tools (e.g., SHAP, LIME) are required, which introduce **extra computational cost and complexity**.

3.7 Cost and sustainability Impact

1. **Hardware Investment Costs:** Efficient parallel computation for credit risk models requires high-performance GPUs (e.g., NVIDIA RTX or A100), increasing initial infrastructure costs. While CPU-based setups are more affordable, they significantly limit model training speed and scalability.
2. **Energy Consumption & Power Costs:** Running large-scale machine learning models on GPU infrastructure increases electricity consumption, especially during hyperparameter tuning and model retraining. This leads to higher operational costs and contributes to increased carbon emissions over time.
3. **Cloud Computing Costs:** Using platforms like AWS, Google Cloud, or Azure for scalable deployment introduces recurring expenses. These include compute instance fees, data storage, and bandwidth, which may become substantial with frequent model usage and large dataset uploads.
4. **Model Training and Maintenance Expenses:** To maintain predictive accuracy, models require periodic retraining with updated financial data, incurring computational and human resource costs. Frequent model evaluation, debugging, and optimization add to ongoing maintenance overhead.
5. **Cost of Data Acquisition and Storage:** Although structured financial datasets are more readily available than medical data, acquiring **high-quality, labeled, and diverse datasets** from reliable sources can involve licensing or subscription fees. Long-term data storage, especially for large-scale historical records, adds cost.
6. **Environmental Impact of AI Computation:** GPU-intensive training sessions significantly increase environmental impact, especially if executed in conventional data centers. The carbon footprint of AI must be minimized through energy-efficient coding practices and optimized batch processing.

7. **Cooling and Thermal Management:** Extended GPU usage leads to considerable heat generation, requiring cooling systems to maintain thermal efficiency. The cost of additional air-conditioning or server room cooling infrastructure impacts both sustainability and budget.
8. **Sustainable AI Practices:** Adopting efficient techniques such as model pruning, quantization, and low-precision training can reduce energy usage. Using green-certified data centers and renewable-powered cloud services promotes sustainable AI development.
9. **Long-Term Economic Viability:** Despite high upfront investment, AI-driven credit scoring systems reduce manual underwriting costs, fraud detection overhead, and loan default risks, making them economically advantageous in the long run by improving risk management efficiency.
10. **Scalability and Deployment Costs:** Deploying the solution across **multiple branches, institutions, or geographies** demands additional investment in standardized hardware, compatible software, and staff training. However, **centralized cloud-based deployment** can ease scale-up efforts.

CHAPTER 4

IMPLEMENTATION

4.1 Environment Setup for Running the Model

GPU Setup & CUDA Installation:

1. Verify CUDA compatibility with your GPU:
nvidia-smi
2. Install CUDA & cuDNN (for PyTorch acceleration):
pip install torch --index-url <https://download.pytorch.org/whl/cu118>

System Monitoring & Resource Management:

1. Track CPU utilization with:

**import psutil
print(psutil.cpu_percent(interval=1))**
2. Optimization & Parallelism:
 - Use **batch size tuning** for improved efficiency.
 - Enable **mixed precision training** with `torch.cuda.amp` for reduced memory usage.

4.2 Sample Implementation Code for Instruction Processing Speed (IPS) for GPU

```
] import time
import numpy as np
from sklearn.ensemble import RandomForestClassifier

# Ensure X_train and y_train are available
if 'X_train' not in locals() or 'y_train' not in locals():
    print("Error: X_train or y_train is missing. Ensure your dataset is loaded properly.")

# Initialize and Train RandomForestClassifier
rf_clf = RandomForestClassifier(n_estimators=100, random_state=42)
rf_clf.fit(X_train, y_train) # Train the model

# Ensure test data is in NumPy format
X_test_np = X_test if isinstance(X_test, np.ndarray) else X_test.to_numpy()

# Function to measure execution time on GPU
def measure_gpu_execution(model, X_test, batch_sizes):
    for batch_size in batch_sizes:
        X_batch = X_test[:batch_size] # Use NumPy array
        start_time = time.time()
        _ = model.predict(X_batch) # Perform prediction
        end_time = time.time()

        elapsed_time = end_time - start_time
        num_operations = X_batch.size * batch_size # Estimate operations

        print(f"Batch Size: {batch_size}, Time Taken: {elapsed_time:.6f} sec, Estimated Instructions: {num_operat

# Define batch sizes
batch_sizes = [1, 32, 64, 128, 256]

# Run GPU execution analysis
print("\n==== Parallel Execution Analysis (GPU) ====")
measure_gpu_execution(rf_clf, X_test_np, batch_sizes)
```

Fig : 4.2.1: Sample code for Instruction Processing Speed (IPS) for GPU

Chapter 5

Experimentation and Result Analysis

Experimental testing of the model in a CPU environment involved varying batch sizes (1, 32, 64, 128, 256) to analyze the impact on execution time and instruction throughput. The results revealed a non-linear trend in processing efficiency as batch size increased.

At **batch size 1**, the model recorded a high latency of **0.009758 seconds**, yielding an **estimated Instruction Processing Speed (IPS)** of approximately 4.92×10^3 instr/sec. This low throughput indicates inefficient computation at minimal batch sizes due to underutilized CPU parallelism.

As batch size increased to **32** and **64**, a significant improvement in IPS was observed— 4.67×10^6 instr/sec and 1.76×10^7 instr/sec, respectively. This indicates better CPU resource utilization and parallel data processing. The peak performance was achieved at **batch size 256**, with the highest IPS of 1.88×10^8 instr/sec and an execution time of **0.016770 seconds**, suggesting optimal balance between data volume and computational workload.

Interestingly, unlike typical GPU execution where performance drops after a certain batch size due to memory limitations, the CPU demonstrated **gradual performance gains up to batch size 256**. However, beyond this point (not tested), memory and cache saturation could become potential bottlenecks.

These observations confirm that increasing batch size enhances instruction throughput on CPUs, though real-time application feasibility remains limited due to relatively slower execution speeds compared to GPU environments. For large-scale or latency-sensitive applications, GPU deployment remains preferable.

```
==== CPU Execution Analysis ====
Batch Size: 1, Time Taken: 0.009758 sec, Estimated IPS: 4.92e+03 instr/sec
Batch Size: 32, Time Taken: 0.010526 sec, Estimated IPS: 4.67e+06 instr/sec
Batch Size: 64, Time Taken: 0.011198 sec, Estimated IPS: 1.76e+07 instr/sec
Batch Size: 128, Time Taken: 0.013447 sec, Estimated IPS: 5.85e+07 instr/sec
Batch Size: 256, Time Taken: 0.016770 sec, Estimated IPS: 1.88e+08 instr/sec
```

Fig 5.1: Instruction Processing Speed (IPS) for CPU

The Fig 5.1 ,represents batch size increases, instruction throughput improves, peaking at 1.88×10^8 IPS for batch size 256.

Despite slight increases in execution time, CPU remains significantly slower than GPU for high-performance tasks.

```
==== Parallel Execution Analysis (GPU) ====  
Batch Size: 1, Time Taken: 0.010648 sec, Estimated Instructions: 4.51e+03 instr/sec  
Batch Size: 32, Time Taken: 0.008846 sec, Estimated Instructions: 5.56e+06 instr/sec  
Batch Size: 64, Time Taken: 0.009788 sec, Estimated Instructions: 2.01e+07 instr/sec  
Batch Size: 128, Time Taken: 0.010864 sec, Estimated Instructions: 7.24e+07 instr/sec  
Batch Size: 256, Time Taken: 0.014195 sec, Estimated Instructions: 2.22e+08 instr/sec
```

Fig 5.2: Instruction Processing Speed (IPS) for GPU

The Fig 5.2, shows GPU execution shows a significant rise in instruction throughput with increasing batch size, peaking at 2.22×10^8 IPS for batch size 256. Despite slight increases in time, GPU consistently outperforms CPU, enabling faster parallel processing for deep learning tasks.

Chapter 6

Conclusion

CONCLUSION

The experimental results of this project clearly demonstrate the effectiveness of leveraging GPU-accelerated parallel computing for large-scale credit risk analysis tasks. Through comparative evaluation, the Random Forest classifier achieved a significantly higher accuracy (98%) over Logistic Regression (65%), highlighting the robustness of ensemble learning techniques in financial risk prediction. Moreover, the system achieved substantial computational performance gains when executing on GPU compared to CPU, particularly as batch sizes increased. At a batch size of 256, the GPU execution reached an estimated throughput of 2.22×10^8 instructions per second, surpassing the CPU's 1.88×10^8 , confirming the value of parallelism and CUDA-based execution in data-intensive machine learning workflows. The results emphasize the importance of optimizing batch size, instruction scheduling, and computational resource utilization for real-time credit scoring applications. This study underscores CUDA's suitability for accelerating machine learning inference while maintaining model accuracy and stability. Future enhancements will include integrating model pruning, feature selection automation, and mixed-precision training to reduce latency and computational overhead. Additionally, extending the framework with support for distributed GPU clusters and scalable memory management techniques will enable real-time analysis in enterprise-grade credit risk environments. Overall, the project validates GPU-based machine learning as a powerful approach for enhancing both predictive performance and system throughput in critical financial decision-making systems.

Chapter 7

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