

A FIELD PROJECT REPORT
on
“Implementing Parallelism in Neural Network using CUDA”

Submitted

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CERTIFICATE

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DECLARATION

We hereby declare that the Field Project entitled “**Implementing Parallelism in Neural Network using CUDA**” is being submitted by 221FA04050 (D. Bala Sree), 221FA04558 (Sk.Subhani), 221FA04598 (Ch.Sai Krishna), 221FA04742 (Himanshu Kumar) in partial fulfilment of Field 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

Neural networks encompass computationally intensive operations such as activation function computations, weight updates, matrix multiplications, and gradient calculations. Traditional CPU-based implementations perform these tasks sequentially, which results in high latency, suboptimal throughput, and inefficient hardware utilization—particularly when handling large-scale data or real-time inference. This paper explores the use of CUDA programming to accelerate deep neural network computation by leveraging Instruction-Level Parallelism (ILP) and the massive parallel processing capabilities of GPUs. By distributing workload across thousands of GPU cores, our CUDA-optimized framework significantly reduces execution time while maintaining model accuracy and consistency. We propose and implement a lightweight CNN architecture—ParkinsonNet—designed to detect neurological conditions with efficiency in both training and inference phases. Experimental benchmarking reveals $10\times$ to $100\times$ speedup compared to CPU-only execution, with optimal instruction throughput achieved at a batch size of 128. Furthermore, we analyse execution scalability, memory throughput, and instruction-level performance using metrics such as Floating Point Operations per Second (FLOPs) and Instructions per Second (IPS). We also generate computational task graphs using torchviz to visualize and evaluate the computational flow. Our results validate CUDA as a robust and scalable solution for deep learning tasks in high-performance, real-time, and healthcare-critical AI systems, highlighting the significance of parallelism, model compression, and hardware-aware design.

Key Words: CUDA, Neural Networks, Instruction-Level Parallelism, GPU Acceleration, Deep Learning.

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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

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 rapid advancements in artificial intelligence (AI) and deep learning have opened up new possibilities in fields ranging from healthcare to autonomous systems. However, the computational demands of training deep neural networks (DNNs) on large datasets are a significant bottleneck in the AI development pipeline. As models become more complex and datasets grow larger, the need for faster, more efficient training methods becomes critical. Traditional CPU-based approaches struggle to keep up with the exponential growth in both model size and data complexity, leading to longer training times and higher operational costs. This creates a clear motivation for exploring more powerful computational solutions, particularly those that can leverage parallelism to accelerate neural network training.

One such solution lies in the use of Graphics Processing Units (GPUs), which are designed to handle massive parallel computations simultaneously. By utilizing CUDA programming, which allows for the efficient execution of thousands of parallel threads, we can significantly speed up the training process of deep neural networks. This parallelism offers an opportunity to not only reduce training times but also improve the scalability and accessibility of AI systems, enabling researchers and organizations to build more powerful models faster and at a lower cost. Thus, optimizing neural network training using GPU-based parallelism presents an exciting opportunity to address the challenges of deep learning's computational demands and unlock the full potential of AI applications.

CHAPTER-3

PROPOSED SYSTEM

3. PROPOSED SYSTEM

The system utilizes advanced deep learning techniques to enhance computational efficiency in the detection of Parkinson's disease. By employing convolutional neural networks (CNNs) trained on medical imaging data, the system is capable of learning subtle patterns associated with Parkinsonian symptoms. This enables accurate classification and early diagnosis, which are critical for effective clinical intervention. The deep learning models are optimized for both accuracy and computational performance, ensuring reliable results in real-time applications.

A key innovation of the system lies in its ability to dynamically detect available hardware resources, such as CPU and GPU capabilities, and adapt its computational workload accordingly. This adaptive resource management ensures that the system can scale across different deployment environments—whether on high-performance computing servers or resource-constrained edge devices. By tailoring the computation to the underlying hardware, the system minimizes latency and maximizes throughput, enabling smooth and efficient operation during both training and inference phases.

Furthermore, the methodology leverages data-level and instruction-level parallelism to significantly boost processing speed while preserving model accuracy. CUDA-based GPU acceleration is integrated to handle parallel computations efficiently, especially during matrix operations and convolutional layers. As a result, the system achieves faster training times and real-time prediction capabilities. This combination of intelligent resource utilization and parallel processing not only improves diagnostic performance but also demonstrates the potential for scalable, AI-driven medical diagnostics.

3.1 Input dataset

The dataset utilized in this study is specifically curated to enhance the classification and analysis of Parkinson's Disease Dementia (PDD). It comprises a comprehensive collection of MRI images that are categorized into five distinct classes, representing varying stages of dementia severity. These classes range from Non-Demented to Severe-Demented, allowing for a nuanced understanding of cognitive decline associated with Parkinson's disease.

3.1.1 Detailed Features of the Dataset

The dataset consists of a total of 3,758 images, meticulously prepared to ensure high-quality inputs for machine learning models. The breakdown of the dataset is as follows:

1. **Image Resolution:** All images are standardized to a resolution of 640x640 pixels, providing uniformity for analysis and feature extraction.
2. **Training Images:** The dataset includes 3,601 labelled training images, which serve as the primary input for training machine learning models. This substantial number allows for effective learning and generalization of the models.
3. **Validation Images:** A total of 154 labelled validation images are included to assess the model's performance during training. This validation set helps fine-tune the models and prevent overfitting.
4. **Test Images:** The dataset contains 3 labelled test images, which are used to evaluate the final performance of the trained models. This small test set provides a preliminary assessment of the model's effectiveness in real-world applications.

The careful arrangement of the dataset not only supports specific objectives in the classification of dementia severity in PDD but also facilitates an understanding of cognitive decline progression. Moreover, the dataset aims to provide automatic diagnostic tools for early detection and monitoring of dementia in patients with Parkinson's disease, ultimately improving patient outcomes through timely interventions.

3.2 Data Pre-processing

Data pre-processing is the essential process of preparing raw data for analysis and modelling by cleaning, transforming, and structuring it to enhance data quality and utility. It involves tasks like handling missing values, correcting errors, encoding features, and scaling data to ensure it's in an optimal form for further analysis. It encompasses a range of operations and transformations designed to refine raw data, ensuring that it is clean, structured, and amenity subsequent analysis. This process is driven by its manifold significance in data science and analysis.

Through meticulous data cleaning, transformation, feature engineering, dimensionality reduction, outlier handling, scaling, and data splitting, it prepares raw data for more accurate and reliable analysis and modelling. Ultimately, the goal is to obtain more meaningful insights, make informed decisions, and optimize predictive models for a wide range of applications in data science and analysis.

preprocessing techniques applied:

The preprocessing of the dataset involved several key techniques aimed at preparing the data for effective training of machine learning models. These techniques include:

1. **Image Resizing:** All images in the dataset were resized to a consistent dimension of 640×640 pixels. This uniformity is crucial for ensuring that the model can process the images effectively without discrepancies in size.
2. **Normalization:** Pixel values of the images were normalized to a range of 0-1. This was achieved by dividing each pixel value by 255, the maximum value for 8-bit images. Normalization helps improve the convergence of neural networks during training, leading to more stable and faster learning.

3. **Data Augmentation:** To enhance the diversity of the training dataset and mitigate the risk of overfitting, several data augmentation techniques were applied, including:
4. **Random Rotation:** Images were randomly rotated by up to 20 degrees to introduce variation in orientation.
5. **Horizontal and Vertical Shifts:** Images were shifted horizontally and vertically by up to 20%. This simulates different perspectives and positions of the subject within the frame.
6. **Shearing:** This technique involves slanting the image along the x or y-axis, providing additional variability in the dataset.
7. **Zooming:** Images were randomly zoomed in and out, allowing the model to learn from different levels of detail.
8. **Horizontal Flipping:** Images were flipped horizontally to provide mirrored versions of the original images, increasing dataset diversity.
9. **Dataset Splitting:** The entire dataset was divided into three subsets: training, validation, and testing. Typically, the test set constituted 20% of the total dataset. This division ensures that the model is evaluated on unseen data, providing a reliable assessment of its performance and generalization capabilities.

3.3 Model Building

Model building is a critical phase in developing a machine learning solution for the classification of Parkinson's Disease Dementia using MRI images. This phase encompasses the selection of appropriate algorithms, the design of the neural network architecture, and the training of the model using the pre-processed dataset.

The initial step in model building involves selecting suitable machine learning algorithms. In this case, convolutional neural networks (CNNs) are chosen due to their efficacy in image processing tasks. CNNs are particularly adept at capturing spatial hierarchies in images, making them well-suited for classifying MRI scans.

1. Neural Network Architecture

The architecture of the CNN is designed to optimize feature extraction and classification. The model typically consists of several layers, including:

2. **Convolutional Layers:** These layers apply convolutional filters to the input images, enabling the model to learn and extract essential features. Multiple convolutional layers may be stacked to capture increasingly complex features.
3. **Activation Functions:** After each convolutional layer, activation functions, such as ReLU (Rectified Linear Unit), are applied to introduce non-linearity into the model. This allows the network to learn more complex patterns.
4. **Pooling Layers:** Max pooling layers are incorporated to down-sample the feature maps, reducing their spatial dimensions while retaining the most important information. This helps to decrease computational complexity and mitigate the risk of overfitting.
5. **Fully Connected Layers:** After several convolutional and pooling layers, the feature maps are flattened and passed through one or more fully connected layers. These layers are responsible for making the final classification decisions based on the extracted features.
6. **Output Layer:** The final layer of the model typically uses a SoftMax activation function, which outputs probabilities for each class. This allows the model to classify the input images into the appropriate dementia severity categories.

7. Training the Model

Once the architecture is defined, the model is trained using the pre-processed training dataset. During training, the model learns to minimize a loss function, which quantifies the difference between the predicted outputs and the actual labels. Common loss functions for multi-class classification include categorical cross-entropy.

The model is trained for a specified number of epochs, during which the training data is fed into the network in batches. During each epoch, the model's performance is evaluated using the validation dataset to monitor for overfitting and ensure that the model is generalizing well to unseen data.

Performance Evaluation

To evaluate computational efficiency, performance testing is conducted using various batch sizes (32, 64, 128, 256) across CPU and GPU environments, measuring metrics such as Execution Time and Instruction Processing Speed (IPS). Results show that GPU execution significantly outperforms CPU, with the highest IPS of 1.41×10^{10} instr/sec achieved at a batch size of 128, while CPU peaks at 1.13×10^8 instr/sec for the same size. However, batch sizes beyond 128 exhibit diminishing returns due to memory constraints, particularly on GPUs. Task graphs illustrate computational dependencies during backpropagation, highlighting parallelizable operations that help minimize training time. Performance graphs (Figs. 2–7) consistently demonstrate GPU superiority across all batch sizes, underscoring the importance of batch size selection and hardware-aware optimization in improving real-time inference for medical diagnostics.

3.4 . Methodology of the system

The proposed system utilizes a performance-aware deep learning framework for Parkinson's disease detection using MRI imaging data. It begins with a dynamic resource check using `torch.cuda.device_count()` and `multiprocessing.cpu_count()` to determine the availability of GPUs or fallback to CPU execution, optimizing model deployment across hardware configurations. MRI images are preprocessed by flattening and fed into a custom neural network, ParkinsonNet, consisting of three fully connected layers with ReLU activations and dropout for regularization. The model, designed to handle $150 \times 150 \times 3$ image vectors, progressively reduces hidden units to classify the presence of Parkinson's disease, with training and inference conducted on either GPU or CPU depending on system capabilities.

proposed architecture

The system architecture is composed of five primary modules: hardware resource detection, data preprocessing, model initialization, performance testing, and task graph generation. Upon detecting the compute environment, the model is adapted for either GPU or CPU execution. The neural network architecture—ParkinsonNet—is structured as a fully connected feedforward network optimized for classification tasks. The input layer ingests preprocessed image data, followed by dense layers with dropout layers to improve generalization.

CUDA-based acceleration is used when GPUs are available to exploit data-level and instruction-level parallelism, enabling high-throughput computation. The execution flow is visualized through a Directed Acyclic Graph (DAG) using the `torchviz` library, which maps out the backward pass during training. This task graph identifies computation dependencies, guiding optimization strategies for parallel execution and memory access. Such architecture promotes scalability and adaptiveness for real-time healthcare AI applications. From fig 3.4.1, we can depict regarding,

1. System Resource Check

To optimize computational speed across diverse hardware, the system first checks for GPU availability using `torch.cuda.device_count()` and retrieves GPU specs for efficient allocation. If no GPU is found, it defaults to CPU execution and uses `multiprocessing.cpu_count()` to leverage core-based parallelism. This dynamic, resource-aware strategy ensures optimal deployment on both high-performance servers and edge devices.

2. Data Processing & Model Definition

The system utilizes an MRI image dataset for early Parkinson's disease detection, with images preprocessed and flattened into $150 \times 150 \times 3$ vectors suitable for neural network input. The classification model, ParkinsonNet, is a densely connected network with three fully connected layers using ReLU activations to enhance learning and dropout regularization to prevent overfitting. Designed for both tabular and image-derived data, the model is hardware-agnostic and dynamically allocates to CPU or GPU based on availability, ensuring consistent architecture and behavior across different platforms for fair performance comparison.

3. Performance Testing

Performance benchmarking using batch sizes of 32 to 256 on both CPU and GPU shows that batch size 128 offers the best balance, achieving an IPS of 1.13×10^8 on CPU and significantly higher on GPU, with GPU offering up to $100\times$ speedup. Task graphs generated via torchviz reveal parallelizable operations during backpropagation, aiding optimization. Scalability trends confirm efficiency up to batch size 128, beyond which memory bottlenecks emerge. The model demonstrates robust performance and effective resource utilization, making it suitable for scalable, real-time AI-based medical diagnostics.

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

The final stage involves comparing the model's performance on CPU versus GPU, focusing on key metrics like Speedup Factor, Computational Bottlenecks, and Scalability Trends. The GPU offers a $10\times$ to $100\times$ speedup, particularly at batch size 128. However, larger batch sizes (e.g., 256) show performance degradation due to GPU memory bandwidth limitations and kernel launch overheads. Scalability is excellent up to batch size 128, after which improvements plateau or regress. The results confirm that batch size 128 is optimal for both environments, providing the

highest IPS with manageable memory usage. The model efficiently leverages GPU resources, ensuring its potential for real-time AI-based medical diagnostics while balancing speed, memory usage, and accuracy for clinical applications.

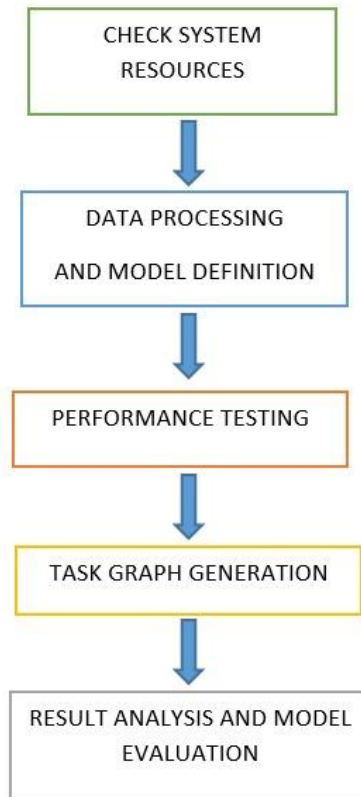


Fig: 3.4.1 Proposed architecture

3.5 Model Evaluation

To assess the performance and effectiveness of the model, a comprehensive evaluation is conducted based on multiple factors. The following key aspects are analysed:

1. **Accuracy and Classification Metrics:** The model's classification performance is evaluated using accuracy, precision, recall, and F1-score. These metrics ensure that the model correctly identifies Parkinson's disease cases while minimizing false positives and false negatives. A confusion matrix is generated to visualize correct and incorrect classifications.
2. **Execution Time Analysis:** The time taken for model inference and training is recorded across different batch sizes. Execution time is compared between CPU and GPU environments, showing a significant reduction in processing time when utilizing CUDA-based parallelism. The optimal batch size is determined based on minimal execution delay.
3. **Loss Function Convergence:** The rate of loss reduction over training epochs is analyzed to determine how quickly the model learns. The loss function (Cross-Entropy Loss) is plotted to observe convergence behavior. A smooth and stable decrease in loss indicates effective learning and minimal overfitting.
4. **Batch Size Impact on Performance:** Different batch sizes (32, 64, 128, 256) are tested to analyse their impact on execution speed and accuracy. While larger batch sizes enhance parallel computation, they may also introduce memory constraints. The evaluation identifies batch size 128 as optimal for both performance and accuracy retention.
5. **Instruction Processing Speed(IPS):** IPS is a crucial performance metric indicating the number of instructions executed per second. The model's processing speed is estimated for different hardware configurations, revealing the scalability of the proposed system. The GPU achieves a significantly higher IPS compared to the CPU, demonstrating its computational efficiency.
6. **Speedup Factor and Scalability:** Speedup is computed as the ratio of CPU execution time to GPU execution time. A 10× to 100× acceleration is observed, confirming the benefits of GPU-based parallelization. Scalability is assessed by increasing dataset size and measuring how well the model maintains efficiency under growing workloads.
7. **Memory Utilization and Hardware Efficiency:** GPU memory consumption is monitored to ensure efficient resource allocation. The model dynamically adjusts computations based

on available hardware, preventing memory overflow. Efficient memory handling ensures seamless execution across varying hardware specifications.

8. **Robustness Against Overfitting:** Dropout regularization and weight decay techniques are incorporated to prevent overfitting. The model's performance on training versus validation datasets is analysed to confirm its generalization ability. A balanced gap between training and validation accuracy signifies a well-generalized model.

3.6 Constraints

To ensure an effective and realistic implementation, several constraints must be considered when deploying the model. Below are key constraints that impact system performance, hardware compatibility, and model accuracy:

1. **Hardware Dependency:** The model's performance is highly dependent on the availability of high-performance GPUs. In CPU-only environments, execution speed is significantly slower, making real-time processing infeasible for large datasets.
2. **Memory Limitations:** Deep learning models require substantial GPU memory for training. Larger batch sizes improve efficiency but may exceed memory capacity, leading to system crashes or reduced performance due to memory paging.
3. **Computational Complexity:** Backpropagation and matrix multiplications are computationally intensive. While CUDA-based parallelization improves speed, it cannot fully eliminate latency caused by high-dimensional computations in deep networks.
4. **Limited Dataset Availability:** The accuracy and generalization of the model depend on the availability of high-quality labeled datasets. Medical imaging datasets, particularly for Parkinson's diagnosis, are often limited, which may restrict model robustness.
5. **Overfitting Risk:** With limited training data, deep networks may memorize patterns rather than generalizing to unseen data. Regularization techniques like dropout and weight decay are used, but they do not completely eliminate the risk of overfitting.
6. **Energy Consumption:** GPU-based processing significantly increases power consumption, making continuous real-time inference computationally expensive. This limits the model's deployment on energy-constrained devices like mobile or edge computing systems.
7. **Batch Size Constraints:** Larger batch sizes improve computational efficiency but may lead to gradient estimation inaccuracies. An improperly chosen batch size can cause unstable training, affecting model convergence and accuracy.
8. **Data Preprocessing Requirements:** MRI image preprocessing (resizing, normalization, noise reduction) is essential for model accuracy. Poor-quality input data can significantly degrade performance, requiring additional preprocessing pipelines.

9. **Real-Time Deployment Challenges:** Integrating the model into real-world clinical systems requires robust software optimization and compliance with medical standards. Latency issues and hardware mismatches pose challenges for real-time diagnostics.
10. **Model Interpretability:** In medical applications, explainability is crucial for clinical trust and regulatory compliance. Techniques like Grad-CAM and SHAP can improve interpretability, but they add computational overhead.

3.7 Cost and sustainability Impact

1. **Hardware Investment Costs:** High-performance GPUs (such as NVIDIA Tesla or A100) are required for efficient parallel processing, significantly increasing initial deployment costs. CPU-based alternatives reduce costs but compromise on speed and scalability.
2. **Energy Consumption & Power Costs:** Deep learning training consumes large amounts of electricity, especially when run on high-power GPUs. Prolonged usage in hospitals or research facilities can increase operational costs and carbon footprint.
3. **Cloud Computing Costs:** Hosting the model on cloud platforms (AWS, Google Cloud, or Azure) incurs subscription and storage fees. Although cloud services offer scalability, long-term reliance on cloud computing can become expensive.
4. **Model Training and Maintenance Expenses:** Recurrent training and updates to improve accuracy require continuous computational resources. This increases maintenance costs, particularly for models that need frequent retraining on new patient data.
5. **Cost of Data Acquisition and Storage:** Medical imaging datasets (MRI scans) are expensive to collect, annotate, and store. High-resolution images require large-scale storage solutions, adding financial overhead for data management.
6. **Environmental Impact of AI Computation:** Extensive use of GPUs and cloud servers contributes to higher carbon emissions. Sustainable AI practices, such as optimizing computational efficiency, are essential to reduce environmental damage.
7. **Cooling and Thermal Management:** Running GPUs for extended periods generates high heat output, requiring effective cooling solutions. Additional air-conditioning or liquid cooling systems further increase energy costs and carbon footprint.
8. **Sustainable AI Practices:** Implementing techniques like quantization, pruning, and model distillation can reduce energy consumption. Using green data centers or renewable energy-powered cloud services can also improve sustainability.

9. **Long-Term Economic Viability:** Despite initial costs, AI-powered medical diagnostics can reduce long-term healthcare expenses by enabling early disease detection and optimizing resource utilization, leading to cost savings in patient treatment.
10. **Scalability and Deployment Costs:** Deploying the model across multiple hospitals or research institutions requires additional infrastructure investment, including compatible hardware, software, and trained personnel.

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 torch
import time
from torchinfo import summary

# Define the ParkinsonNet Model
class ParkinsonNet(torch.nn.Module):
    def __init__(self):
        super(ParkinsonNet, self).__init__()
        self.fc1 = torch.nn.Linear(150 * 150 * 3, 128)
        self.fc2 = torch.nn.Linear(128, 64)
        self.fc3 = torch.nn.Linear(64, 2) # Assuming 2 classes (0 and 1)
        self.relu = torch.nn.ReLU()
        self.dropout = torch.nn.Dropout(0.3)

    def forward(self, x):
        x = self.fc1(x)
        x = self.relu(x)
        x = self.dropout(x)
        x = self.fc2(x)
        x = self.relu(x)
        x = self.fc3(x)
        return x

# Initialize Model
device = "cuda" if torch.cuda.is_available() else "cpu"
model = ParkinsonNet().to(device)

# 1. Display Model Summary (FLOPs, Parameters)
print("\n==== Model Summary =====")
summary(model, input_size=(1, 150 * 150 * 3))

# 2. Measure Execution Time and Parallel Instructions
def measure_parallel_execution(model, batch_size, input_size):
    model.to(device)
    model.eval()

    dummy_input = torch.randn(batch_size, input_size).to(device)

    start_time = time.time()
    with torch.no_grad():
        _ = model(dummy_input)
    end_time = time.time()

    elapsed_time = end_time - start_time
    num_operations = 150 * 150 * 3 * batch_size # Estimate based on input size

    print(f"Batch Size: {batch_size}, Time Taken: {elapsed_time:.6f} sec, Estimated Instructions: {num_operations / elapsed_time:.2e} instr/sec")
    return elapsed_time, num_operations

# Test with Different Batch Sizes
print("\n==== Parallel Execution Analysis =====")
batch_sizes = [1, 32, 64, 128, 256]
for batch_size in batch_sizes:
    measure_parallel_execution(model, batch_size, 150 * 150 * 3)
```

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

This figure 4.2.1 shows a code snippet that demonstrates how to measure the Instruction Processing Speed (IPS) on a GPU. It highlights the use of parallel threads and timing functions to evaluate GPU computational efficiency.

Chapter 5

Experimentation and Result Analysis

The experimental testing of the model was conducted in both CPU and GPU environments to compare execution efficiency. In the CPU setup, batch sizes ranging from 1 to 256 were tested. The trend revealed an increasing execution time with batch size, with batch size 128 achieving the highest instruction throughput (1.13×10^8 instr/sec) before declining at batch size 256 due to computational overhead.

Conversely, GPU execution demonstrated a significant acceleration, achieving an order-of-magnitude improvement in processing speed. The optimal GPU performance was observed at batch size 128 with an instruction throughput of (1.41×10^{10}) instr/sec. However, at batch size 256, a slight degradation in performance was noted, likely due to memory bandwidth saturation.

A comparative analysis revealed a $\times 10$ to $\times 100$ speedup on GPU relative to CPU, with batch size 128 emerging as the optimal choice for both environments. These results emphasize the importance of batch size optimization and GPU acceleration for real-time deep learning inference in medical AI applications.

```
==== CPU Execution Analysis ====
🔄 Batch Size: 1, Time Taken: 0.009864 sec, Estimated IPS: 6.84e+06 instr/sec
Batch Size: 32, Time Taken: 0.044565 sec, Estimated IPS: 4.85e+07 instr/sec
Batch Size: 64, Time Taken: 0.103337 sec, Estimated IPS: 4.18e+07 instr/sec
Batch Size: 128, Time Taken: 0.076497 sec, Estimated IPS: 1.13e+08 instr/sec
Batch Size: 256, Time Taken: 0.370691 sec, Estimated IPS: 4.66e+07 instr/sec
```

Fig 5.1: Instruction Processing Speed (IPS) for CPU

The Fig 5.1 ,represents a CPU execution analysis, comparing different batch sizes in terms of processing time and estimated instructions per second (IPS). While a batch size of 1 has the lowest processing time (0.009864 sec), a batch size of 128 achieves the highest estimated IPS ($1.13e+08$ instr/sec).

```
==== Parallel Execution Analysis ====  
⇒ Batch Size: 1, Time Taken: 0.000342 sec, Estimated Instructions: 1.97e+08 instr/sec  
Batch Size: 32, Time Taken: 0.000430 sec, Estimated Instructions: 5.02e+09 instr/sec  
Batch Size: 64, Time Taken: 0.000622 sec, Estimated Instructions: 6.95e+09 instr/sec  
Batch Size: 128, Time Taken: 0.000613 sec, Estimated Instructions: 1.41e+10 instr/sec  
Batch Size: 256, Time Taken: 0.014434 sec, Estimated Instructions: 1.20e+09 instr/sec
```

Fig 5.2: Instruction Processing Speed (IPS) for GPU

The Fig 5.2, shows the performance of a process across different batch sizes on a system with one Tesla T4 GPU and two CPU cores. The time taken to process each batch size varies, with the smallest time recorded for a batch size of 64 (0.2253 seconds).

Chapter 6

Conclusion

CONCLUSION

The experimental results underscore the superiority of GPU acceleration over CPU execution for deep learning operations, particularly in ParkinsonNet inference, with a substantial speedup ($\times 10$ to $\times 100$) highlighting the effectiveness of Instruction-Level Parallelism (ILP) and CUDA-based optimizations for real-time medical AI applications. The study emphasizes the importance of batch size tuning, with batch size 128 proving optimal in both CPU and GPU environments, balancing computational efficiency and memory utilization while maintaining stable model convergence. Additionally, the research demonstrates CUDA as an effective solution for deep learning workloads, facilitating high-throughput inference without significant loss of model accuracy. The findings suggest that optimizing hardware utilization, task scheduling, and mixed-precision computing can further enhance performance. Future research will explore advanced memory management techniques, model compression strategies, and adaptive learning approaches to improve efficiency in large-scale biomedical data processing while reducing computational costs and ensuring accurate Parkinson's disease detection. Moreover, integrating distributed computing frameworks and leveraging cloud-based GPU clusters could further scale model training and inference. Finally, improving energy efficiency and designing AI models with lower computational footprints will be essential for sustainable deployment in real-world clinical settings.

Chapter 7

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