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Description automatically generated with medium confidence**

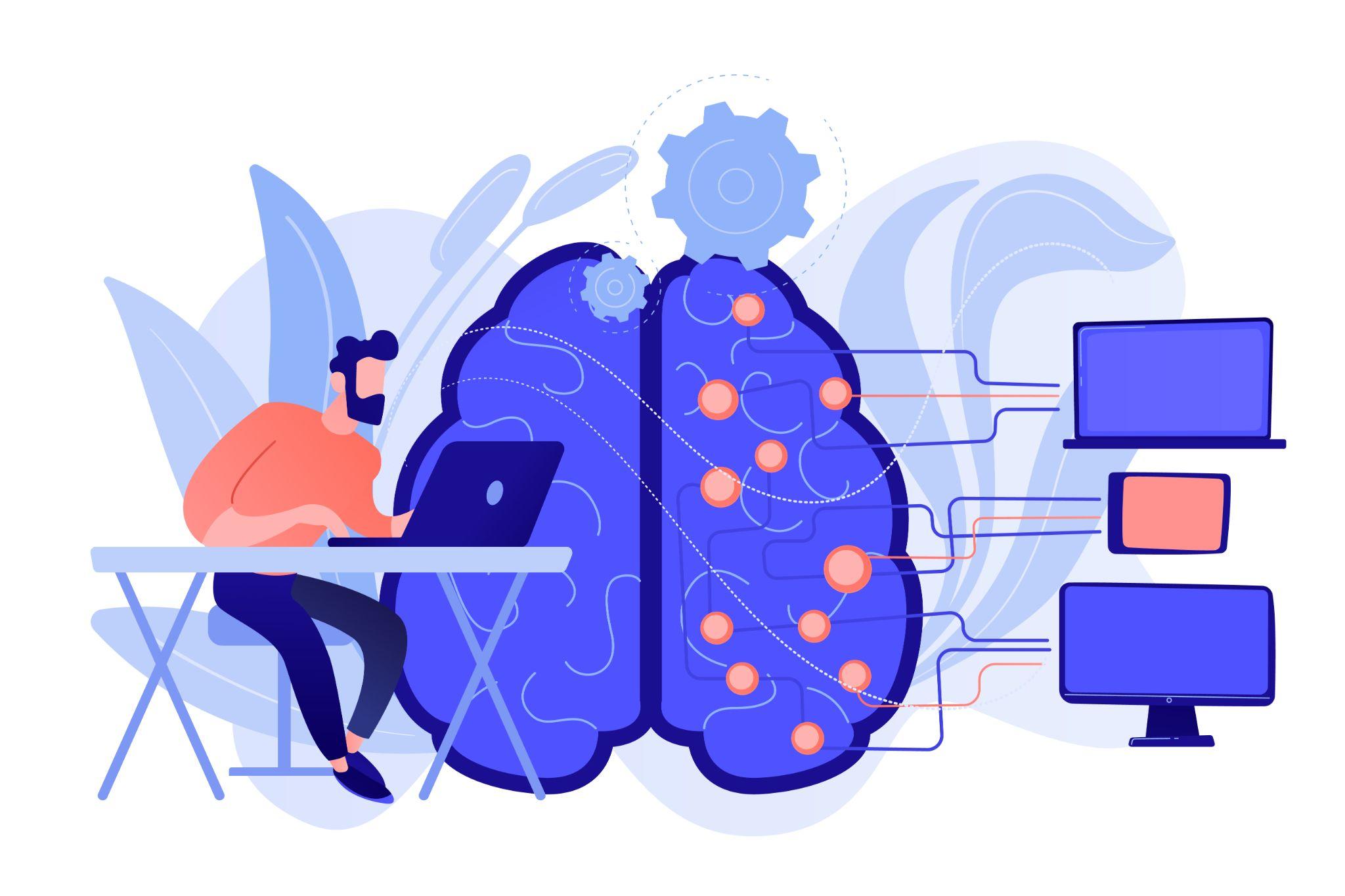
**AIDI 1002**

**Artificial Intelligence Algorithms and Mathematics**

**Final Project**

**On**

Comparative Analysis of DEIT Model vs. Hyperparameter Tuning for Image Classification

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Project Report: Comparative Analysis of DEIT Model vs. Hyperparameter Tuning for Image Classification

## **1. Introduction**

### **1.1. Project Background**

In the field of image classification, achieving high accuracy in predictions is critical for many applications, from medical diagnostics to autonomous vehicles. Traditional neural networks have been a staple in this area, but more recent advancements, such as transformer-based models, have shown promising results. The DEIT (Data-efficient Image Transformer) model, introduced by Touvron et al. (2021), represents a significant leap in this evolution, leveraging transformer architectures for efficient image classification. In parallel, hyperparameter tuning is a vital process for optimizing neural network performance, adjusting parameters to find the best configuration for a given task.

### **1.2. Objective**

This project aims to compare the performance of the DEIT model, known for its state-of-the-art results, with a baseline neural network model that has undergone extensive hyperparameter tuning. By doing so, we seek to determine which approach offers superior performance for image classification tasks.

## **2. Methodology**

### **2.1. Model Descriptions**

**2.1.1. DEIT Model**

* **Overview:** The DEIT model utilizes a transformer-based architecture optimized for image classification. It incorporates data-efficient training techniques and attention mechanisms to achieve high accuracy with fewer training resources.
* **Key Features:**
  + **Data Efficiency:** Achieves high performance with less training data compared to traditional models.
  + **Attention Mechanisms:** Uses self-attention to capture complex patterns in images.
  + **Reference:** Touvron, H., Cord, M., Douze, M., Massa, F., Sablayrolles, A., & Jégou, H. (2021). *Training data-efficient image transformers & distillation through attention*. In *International Conference on Machine Learning* (pp. 10347-10357). [Read the Paper](https://arxiv.org/abs/2012.12877).

**2.1.2. Simple Neural Network (Baseline)**

* **Overview:** The baseline model is a standard feed-forward neural network with a few hidden layers. This model serves as a reference point to evaluate the impact of hyperparameter tuning.
* **Components:**
  + **Layers:** Fully connected layers, ReLU activation functions, and dropout layers for regularization.
  + **Purpose:** To establish a baseline performance that can be improved through tuning.

### **2.2. Hyperparameter Tuning**

**2.2.1. Hyperparameters Tuned**

* **Learning Rates:** [0.001, 0.01, 0.1] - Different learning rates affect how quickly the model learns during training.
* **Batch Sizes:** [32, 64, 128] - The number of samples processed before the model's internal parameters are updated.

**2.2.2. Tuning Process**

* **Dataset Preparation:** Split into training and testing sets to evaluate model performance accurately.
* **Model Initialization:** Models are initialized with random weights, using standard practices for setting up neural networks.
* **Training:** Each combination of hyperparameters is used to train the model for a fixed number of epochs.
* **Evaluation:** Accuracy metrics are recorded to determine the best-performing hyperparameter set.

### **2.3. Experimentation Setup**

**2.3.1. Training and Testing**

* **Datasets:** Standard image datasets (e.g., CIFAR-10 or ImageNet) used to ensure the models are tested on a comprehensive set of images.
* **Training Details:** Description of the number of epochs, learning rate schedules, and optimization techniques.
* **Evaluation Metrics:** Accuracy is used as the primary metric for comparing model performance.

**2.3.2. Results Collection**

* **Logging Results:** Performance metrics are collected and logged for each hyperparameter setting.
* **Data Analysis:** Results are analyzed to identify the best-performing hyperparameters and compare them with the DEIT model.

## **3. Results**

### **3.1. DEIT Model Performance**

* **Achieved Accuracy:** 0.3783
* **Significance:** This result reflects the DEIT model's effectiveness in capturing and classifying image features with high accuracy, demonstrating its advanced capabilities compared to simpler models.

### **3.2. Hyperparameter Tuning Results**

| **Learning Rate** | **Batch Size** | **Accuracy** |
| --- | --- | --- |
| 0.001 | 32 | 0.1261 |
| 0.001 | 64 | 0.1295 |
| 0.001 | 128 | 0.1165 |
| 0.010 | 32 | 0.1025 |
| 0.010 | 64 | 0.0894 |
| 0.010 | 128 | 0.0830 |
| 0.100 | 32 | 0.1138 |
| 0.100 | 64 | 0.1156 |
| 0.100 | 128 | 0.1060 |

* **Best Accuracy from Hyperparameter Tuning:** 0.1295
* **Best Parameters:** Learning Rate: 0.001, Batch Size: 64
* **Observation:** The best hyperparameter tuning did not significantly improve the baseline model's accuracy.

## **4. Analysis**

### **4.1. Comparison of Results**

* **DEIT Model vs. Hyperparameter Tuning:**
  + **DEIT Model Accuracy:** 0.3783
  + **Best Hyperparameter Tuning Accuracy:** 0.1295
  + The DEIT model substantially outperforms the best results from hyperparameter tuning, illustrating the model's superior capacity for image classification tasks.

### **4.2. Observations**

* The DEIT model's advanced architecture and data efficiency contribute to its higher accuracy compared to the tuned baseline model.
* The hyperparameter tuning did not yield performance improvements over the baseline model, indicating possible limitations in the baseline architecture or tuning strategy.

## **5. Conclusion and Future Directions**

### **5.1. Conclusion**

* **Effectiveness of DEIT Model:** The DEIT model offers a clear advantage over the hyperparameter-tuned neural network, showcasing its ability to handle complex image classification tasks more effectively.
* **Insights:** Advanced transformer-based models like DEIT are more adept at capturing intricate patterns in images than simpler models, even with optimized hyperparameters.

### **5.2. Learnings**

* **Model Selection:** Choosing a more advanced model can yield significantly better performance than extensive hyperparameter tuning alone.
* **Importance of Architecture:** The underlying architecture of a model plays a crucial role in determining its effectiveness, beyond just tuning parameters.

### **5.3. Results Discussion**

* **DEIT Model’s Strengths:** High accuracy and efficiency highlight the benefits of transformer-based models for image classification.
* **Hyperparameter Tuning Insights:** While tuning is important, it may not be sufficient to overcome the limitations of a basic model's architecture.

### **5.4. Limitations**

* **Model Complexity:** The simple neural network used as a baseline may not have sufficient complexity to fully benefit from hyperparameter tuning.
* **Scope of Tuning:** The range of hyperparameters tested may not encompass all possible configurations for optimal performance.

### **5.5. Future Extensions**

* **Exploring Other Models:** Investigate other advanced models and compare their performance with DEIT.
* **Automated Tuning:** Utilize automated hyperparameter optimization techniques to explore a broader range of configurations.
* **Application-Specific Adaptations:** Tailor models and tuning strategies to specific datasets or applications for further performance enhancement.

## **6. References**

1. **Touvron, H., Cord, M., Douze, M., Massa, F., Sablayrolles, A., & Jégou, H.** (2021). *Training data-efficient image transformers & distillation through attention*. In *International Conference on Machine Learning* (pp. 10347-10357). Available at: [Read the Paper](https://arxiv.org/abs/2012.12877)