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(Autonomous College Affiliated to the University of Mumbai)
NAAC ACCREDITED with "A" GRADE (CGPA : 3.18)

DEPARTMENT OF INFORMATION TECHNOLOGY

COURSE NAME: Machine Learning Laboratory **COURSE CODE:** DJS22ITL602

CLASS: Third Year B.Tech **SEM:** VI

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EXPERIMENT NO. 8

CO Measured:

CO3 – Apply various machine learning techniques

TITLE: Mini Project: Stage II

AIM / OBJECTIVE: Mini Project

Step 4: Training using Machine Learning Model
Step 5: Evaluating Model Performance

DESCRIPTION OF EXPERIMENT:

In this mini project you are expected to choose any algorithm in machine learning with respect to some use case of your choice. It can be a small-scale project where you apply machine learning algorithms to a specific dataset to solve a problem, often focusing on a single concept or technique, typically used for learning purposes and usually involving data collection, cleaning, feature engineering, model training, and evaluation within a manageable scope.

Key characteristics of a mini machine learning project to consider in this experiment:

Step 4 -Training using Machine Learning Model:

Splitting the Data:

The preprocessed dataset was divided into:

- **Training set (70%)** for model learning.
- **Validation set (20%)** for tuning and early stopping.
- **Test set (10%)** for final evaluation.

Selecting a Model:

The **Vision Transformer (ViT)** was selected due to its advantages over traditional CNNs in capturing long-range dependencies in visual features and its compatibility with transformer-based multimodal architectures. ViT's patch-based self-attention allows efficient extraction of semantic context from complex images in the VQA setting.

Training the Model:

1. **Input Alignment for VLM**
   The model required both visual and textual inputs to be appropriately preprocessed and aligned:
   - **Textual Preprocessing**:
     - Questions from the VQA 2.0 dataset were **gender-neutralized** to reduce bias from the language modality.
     - Tokenization was applied to convert the text into model-readable tokens.
   - **Visual Preprocessing**:
     - Images from the COCO 2014 dataset were **resized**, **converted to tensors**, and **normalized**.
     - These were then passed through a **Vision Transformer (ViT)** encoder to obtain high-level visual embeddings.
2. **Feature Extraction**
   - **Textual features** were embedded using a language encoder.
   - **Visual features** were extracted via the ViT model, capturing spatial and semantic information across image patches.
3. **Model Architecture**
   - The architecture combined **ViT-based visual features** and **tokenized question embeddings**.
   - A **fusion mechanism** was employed to merge these modalities, typically via concatenation or transformer-based cross-attention.
4. **Training Objective**
   - The model was trained to **predict the correct answer** to each question.
   - **Cross-entropy loss** was used as the objective function.
   - **Adam optimizer** was employed to minimize the loss function with learning rate scheduling for stable convergence.
5. **Bias Mitigation Integration**

- During training, **preprocessed gender-neutral questions** were used to reduce learned bias from the textual modality.
- Model predictions were later statistically tested for bias using the **Chi-square test**, ensuring that the training strategy led to more fair and unbiased outputs.

6. **Regularization & Optimization**
    - Dropout layers and weight decay were applied to reduce overfitting.
    - Training was monitored using **validation accuracy and loss**, with early stopping to prevent overfitting.

Hyperparameter Tuning:

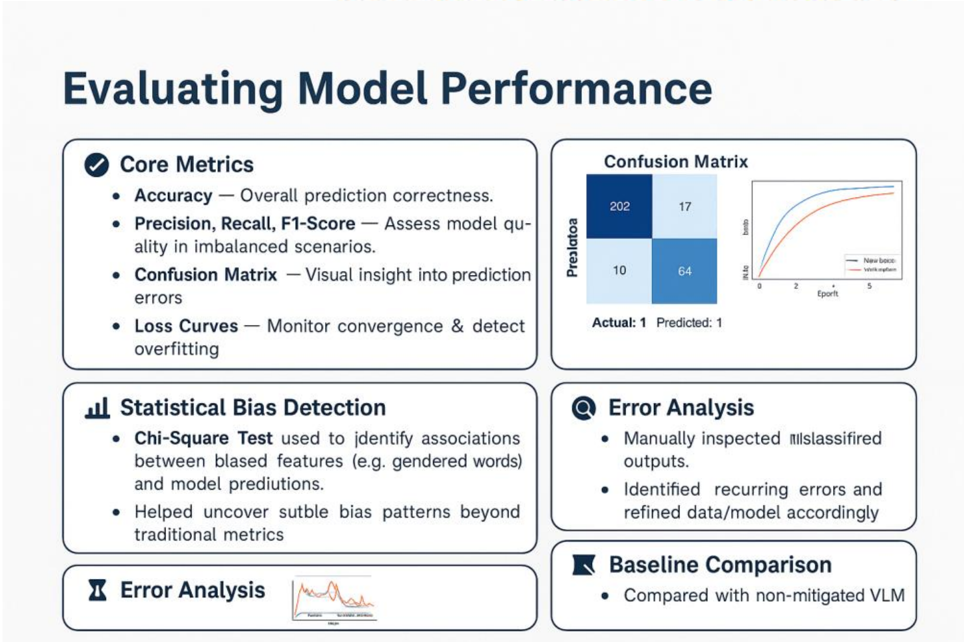
To optimize the model's performance and ensure stable training, we performed **hyperparameter tuning** through the following steps:

1. **Parameters Tuned**:
    - **Learning Rate**: Critical for convergence speed and stability.
    - **Batch Size**: Balanced memory usage and gradient stability.
    - **Number of Epochs**: Tuned to avoid overfitting or underfitting.
    - **Dropout Rate**: Controlled overfitting during training.
    - **Weight Decay**: Regularization parameter to reduce complexity.
2. **Tuning Methodology**:
    - We used a **Grid Search** approach to systematically evaluate combinations of hyperparameters across predefined ranges.
    - Each configuration was assessed using validation accuracy and loss.
3. **Evaluation Metric**:
    - **Validation Loss** and **F1-score** (for imbalanced outputs) were the primary metrics for selecting optimal parameters.
    - Early stopping was employed to halt training once no significant improvement was observed over successive epochs.
4. **Final Configuration**:
    - Learning Rate: 3e-5
    - Batch Size: 16
    - Epochs: 10
    - Dropout Rate: 0.3
    - Optimizer: Adam with weight decay

Step 4 -Evaluating Model Performance:

After training, the model's performance is assessed to ensure it generalizes well to unseen data. The evaluation process involves:

Performance Metrics:



Validation Techniques:

To ensure that our model generalizes well and avoids overfitting, the following validation strategies were applied:

- **Train-Validation-Test Split**:
  The dataset was split into training (70%), validation (20%), and test (10%) sets.
  This allowed for proper tuning of hyperparameters and unbiased final evaluation.
- **k-Fold Cross-Validation**:
  We used k-fold cross-validation (typically k = 5 or 10) to validate the robustness of our model across different data subsets.
  This technique helped mitigate overfitting and provided a more reliable estimate of model performance.
- **Early Stopping**:
  To prevent overfitting during training, early stopping was employed based on validation loss, halting training when no improvement was observed after a certain number of epochs.
- **Hyperparameter Tuning Feedback Loop**:
  Validation performance was used as feedback during hyperparameter tuning (e.g., learning rate, batch size), guiding model refinement before final testing.

Bias-Variance Trade-off Analysis:

In our work, we aimed to ensure a balance between model complexity and generalization, especially given the nuanced task of detecting and mitigating subtle biases in VLM outputs. The following insights guided our analysis:

- **Bias**:
  A high-bias model tends to overlook subtle patterns in multimodal data, such as nuanced visual-question interactions, leading to underfitting.
  By using ViT-based visual encoders and robust text encoders, we ensured sufficient model capacity to capture complex visual-linguistic relationships and potential bias signals.
- **Variance**:
  VLMs with large capacity are prone to overfitting, especially on unbalanced or noisy datasets.
  To reduce variance:
  - Regularization methods were applied during training.
  - Cross-validation and early stopping prevented over-training.
  - Visual input was normalized, and textual input was cleaned and neutralized, reducing noise.
- **Final Trade-off**:
  Our approach strikes a balance:
  - The model does not overly generalize (low bias), as evidenced by its ability to detect nuanced bias patterns.
  - It also avoids overfitting (low variance), confirmed by consistent validation and test set performance.
  - Bias mitigation techniques further improved generalization, reducing unintended variance due to demographic imbalance in data.

PROCEDURE:

1. Train the selected model using appropriate techniques and optimize hyper-parameters.

2. Evaluate the model’s performance using relevant metrics and compare results with other models.

OBSERVATIONS / DISCUSSION OF RESULT:

1. What are hyper-parameters in machine learning? And Which hyper-parameters significantly impact model performance?
2. How do hyper-parameters affect overfitting and underfitting?

CONCLUSION:

Base all conclusions on your actual results; describe the meaning of the experiment and the implications of your results.

REFERENCES:

(List the references as per format given below and citations to be included the document)

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[2]https://developers.google.com/machine-learning/guides/text-classification/step-5

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