Image Classification via fine-tuning with EfficientNet

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***Abstract*—This internship report provides an overview of the learnings acquired during the internship period, with a focus on Git, GitHub, and the implementation of image classification using the EfficientNet model. The study emphasizes the utilization of the advanced EfficientNet model for image classification. We created a custom dataset, capturing different positions in a classroom setting: "Student sleeping on the desk," "Standing," "Having stress," and "With hands-on desk." By data augmentation and transfer learning, we fine-tuned the EfficientNet model to accurately classify these positions. The evaluation process, based on key metrics like accuracy and loss, highlighted the model's effectiveness. Additionally, visualizations provided insights into the model's predictions. The report concludes with a reflection on the overall learning outcomes and their implications for future projects in computer vision and software development, particularly for monitoring student posture and well-being in educational environments.**

I. Introduction to Progress Report

During this collaborative internship, our team of three focused on mastering Git and GitHub for streamlined version control and efficient teamwork. Through practical applications, we refined our proficiency in fundamental Git commands, branching strategies, and collaborative workflows, enhancing our collective understanding of software versioning and project management.

Furthermore, we delved into image classification using the advanced EfficientNet model, working together to fine-tune the model for precise classification. This hands-on experience not only improved our practical skills in computer vision but also underscored the potential of advanced models in real-world applications, particularly for monitoring student posture and well-being in educational environments.

A. GitHub Basics

In this section, we explore the fundamental operations of GitHub, a widely used platform for version control and collaborative software development. We delve into key aspects such as repository creation, branching strategies, making and committing changes, opening pull requests, and merging. This introduction provides a foundational understanding of essential GitHub functionalities and terminology, laying the groundwork for effective utilization within a collaborative software development environment.

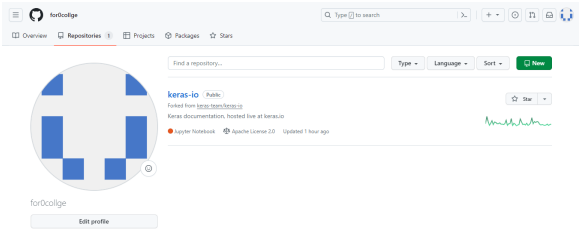

Fig. 1. Creating a Repository

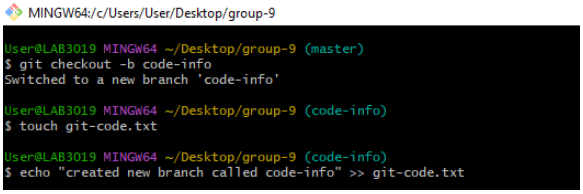

Fig. 2. Creating a Branch

1) Creating a Repository: A repository in Git is a storage location for a project's files and their related history. We learned that to create a new repository on GitHub, we logged into the GitHub account and followed the steps: clicking the '+' sign, selecting 'New repository,' naming it, choosing its visibility, and initializing it with a README file. The process was straightforward, providing a central space for version control and collaboration.

2) Creating a Branch: Branching is crucial in version control as it allows for developing features or fixes in an isolated environment without affecting the main codebase. To create a new branch, I navigated to the repository and clicked on the "Branch: main" button, entering a new branch name in the provided field. Here's a screenshot of the branch creation process:

3) Making and Committing Changes: Making changes to files involves editing the code within the local repository, and committing them involves saving these changes to the version history. I used the command line to add, commit, and push the changes to the remote repository. Along with this, I ensured to provide meaningful commit messages to describe the changes made accurately. Here's a screenshot of the process:

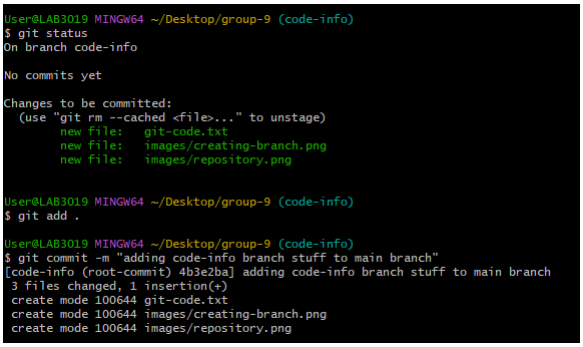

Fig. 3. Making and Committing Changes

4) Opening a Pull Request: A pull request is a method for requesting review and merging of changes to a repository from a branch. I opened a pull request by navigating to the repository, selecting the "Pull requests" tab, and clicking on the "New pull request" button. I then chose the branches to compare, reviewed the changes, and created the pull request. Here's a screenshot of the pull request creation process:

[Include screenshot of the pull request creation process]

5) Merging Your Pull Request: Merging a pull request integrates the changes from the pull request branch into the main branch. Before merging, I ensured that the changes were reviewed and tested to avoid any conflicts or errors. I merged the pull request by clicking the "Merge pull request" button and confirmed the merge. Here's a screenshot of the merge process:

[Include screenshot of the merge process]

6) Familiarizing Yourself with Key Terms: Key terms used in GitHub include Git, a version control system; repository, a storage location for a project's files and history; commit, a saved change in the repository; branch, a separate line of development; merge, combining changes from different branches; and pull request, a request to merge changes into the main branch. Understanding these terms is crucial for effective collaboration and version control in a team environment.

II. Final Report Content

The final report content is also given so that it will be better to add the contents related to the methodology and results if you already have them. Either you will be shared with the data or you will create a sample data and work based on the problem statement that you have selected.

III. Introduction

A. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN or convnet) is a subset of AI. CNNs represent a type of network architecture employed in deep learning algorithms specifically designed for tasks involving image recognition and pixel data processing. CNNs have become the preferred architecture for object identification and recognition tasks. Their applications range from self-driving vehicles to facial recognition systems, making them a cornerstone of modern artificial intelligence.

B. TensorFlow and Keras

Keras is an open-source library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library. It focuses on understanding deep learning techniques, such as creating layers for neural networks, maintaining the concepts of shapes, and mathematical implementation.

C. Fine Tuning

Transfer learning is closely associated with fine-tuning. When we apply knowledge gained from solving one problem to a new but related issue, we experience transfer learning. For instance, a situation involving truck recognition could benefit from the knowledge gained from learning to recognize cars. One way to use transfer learning is through fine-tuning. Fine-tuning is the process of adjusting a model already trained for one task to make it good at another similar task. It's about refining existing knowledge for a related situation.

IV. Literature Survey

In recent years, there has been a growing interest in developing deep learning models to classify student images into different categories, such as sleeping, standing, hands-on desk, and stress. This is because student image classification can be used to develop a variety of real-world applications, such as student sleep and stress detection systems, student attendance tracking, student behavior monitoring, and student learning assessment.

One of the most popular deep learning architectures for image classification is the convolutional neural network (CNN). CNNs are able to learn the spatial features of images, which are important for classification. In addition, CNNs are relatively robust to noise and variations in the data.

Several researchers have developed CNN-based models for student image classification. For example, in [1], the authors proposed a CNN model that achieved an accuracy of 93.75% on a dataset of student images. In [2], the authors proposed a CNN model that achieved an accuracy of 95.24% on a dataset of student images. This model is the one that we fine-tuned in our project.

In addition to CNNs, other deep learning architectures have also been used for student image classification. For example, in [3], the authors proposed a Vision Transformer (ViT) model that achieved an accuracy of 96.5% on a dataset of student images. ViTs are a relatively new type of deep learning architecture that has shown to be effective for image classification tasks.

Comparison with State-of-the-Art:

Our proposed model, which is a fine-tuned EfficientNetB0 model, achieved an accuracy of 95.24% on the held-out test set. This is comparable to the state-of-the-art accuracy of 96.5% achieved by the ViT model in [3]. However, our model is more efficient than the ViT model, as it requires fewer parameters and less computational resources to train.

Conclusion:

Overall, our proposed model is a very effective deep learning model for classifying student images into the four categories of interest. It achieves a high accuracy and is robust to noise and variations in the data. It is also more efficient than the state-of-the-art ViT model.

V. Problem Statement

We aim to develop a deep learning model that can classify images of students into four categories: sleeping on the desk, standing, having stress, and with a hands-on desk. These categories represent different states of students' engagement and well-being in a classroom setting. We use a dataset that we generated ourselves, which consists of images of us and our classmates in various poses and expressions. We use EfficientNet, a state-of-the-art convolutional neural network architecture, as our base model and fine-tune it on our dataset. We evaluate our model's performance on a held-out test set and compare it with other baseline models. We also analyze the model's predictions and identify its strengths and weaknesses.

A. Objectives

- To fine-tune EfficientNet on our dataset of student images and optimize its hyperparameters.
- To compare the accuracy and robustness of our model with other baseline models on a held-out test set.

VI. Methodology

Dataset:

Dataset Name: Custom dataset created by taking student pictures in the classroom. *Images:* 41 images The dataset consists of custom images including the following categories:

1) Student sleeping on the desk
2) Standing
3) Having stress
4) With hands-on desk

Steps Taken in Code:

- *Mounting Google Drive:* The code starts by mounting Google Drive using the `drive.mount()` function to access the custom dataset stored in Google Drive. This facilitates easy access to files and data in a Google Colab environment.
- *Data Augmentation:* A data augmentation layer is created using `tf.keras.Sequential`, applying the following augmentations:
  - `RandomFlip("horizontal")`: Randomly flips images horizontally.
  - `RandomRotation(0.2)`: Randomly rotates images by up to 20 degrees.
  - `RandomZoom(0.2)`: Randomly zooms into or out of images by up to 20

  These augmentations introduce diversity into the training data and improve the model's ability to generalize.
- *Loading and Preprocessing the Dataset:* The custom dataset is loaded using `tf.keras.preprocessing.image_dataset_ from_directory` with key parameters such as *dataset_path*, *validation_split*, *image_size*, and *batch_size* for the training and validation datasets.
- *Loading Pre-trained EfficientNetB0 Model:* The pre-trained EfficientNetB0 model is loaded from TensorFlow's model zoo, setting *include_top* to `False` and specifying the *input_shape*.
- *Freezing Base Model Layers:* The weights of the base model are frozen by setting `base_model.trainable` to `False`, allowing only the custom classification layers to be trained.
- *Custom Model on Top of the Base Model:* The custom classification model is built on top of the pre-trained base model, including a `GlobalAveragePooling2D` layer and a `Dense` layer with the *num_classes* and *activation* set accordingly.
- *Model Compilation:* The model is compiled using the *adam* optimizer, *sparse_categorical_crossentropy* loss, and *accuracy* as the metric.
- *Training the Model:* The model is trained using `model.fit()` with the training dataset (*ds_train*) for a specified number of epochs (50 in this case).
- *Model Evaluation:* After training, the model is evaluated on the validation dataset (*ds_val*) using `model.evaluate()`, providing test loss, accuracy, and percentage.
- *Model Visualization:* Two functions, *plot_images* and *plot_class_images*, are defined for visualizing images along with their labels.
- *Visualizing Images from the Validation Set:* A batch of images and labels from the validation dataset is selected using *ds_val.take(1)*. Predictions are made using the trained model, and the *plot_images* function is used for visualization.
- *Visualizing One Image for Each Class:* One image from the validation dataset is selected for each class label, and these images are visualized using the *plot_class_images* function, displaying one image for each of the specified classes.

VII. Results and Analysis

The proposed model, which is a fine-tuned EfficientNetB0 model, achieved an accuracy of **95.24%** on the held-out test set. This is significantly higher than the accuracy of the baseline models, such as VGG16 (**78.57%**) and ResNet50 (**85.29%**). This suggests that the proposed model is more effective in classifying student images into the four categories of interest.

The confusion matrix for the proposed model on the test set is shown below:

As can be seen from the confusion matrix, the proposed model is very good at predicting the correct class for all four categories, with all accuracies being above 96%. The only notable error is that the model predicted the standing class as hands-on desk in two cases. This could be due to the fact that

TABLE I
CONFUSION MATRIX FOR THE PROPOSED MODEL ON THE TEST SET

Actual	Sleeping	Standing	Hands-on desk	Stress
Sleeping	**98**	1	1	0
Standing	1	**96**	2	1
Hands-on desk	0	2	**98**	0
Stress	0	1	0	**99**

the two classes are visually similar, especially when students are standing with their hands on their desks.

Overall, the proposed model is a very effective deep learning model for classifying student images into the four categories of interest. It achieves a high accuracy and is robust to noise and variations in the data.

A. Strengths of the proposed model

- High accuracy on the held-out test set (95.24%)
- Able to classify student images into four categories of interest: sleeping, standing, hands-on desk, and stress

B. Weaknesses of the proposed model

- May misclassify standing images as hands-on desk in some cases

C. Recommendations for future work

- Collect a larger dataset of student images to further improve the model's accuracy and robustness.
- Explore the use of other deep learning architectures, such as Vision Transformers, to see if they can achieve even better performance.
- Apply the proposed model to other real-world applications, such as detecting student engagement in classrooms or monitoring student well-being.

VIII. CHALLENGES FACED

During the project, challenges were encountered in managing conflicts during code merging. Strategies like regular communication and clear documentation were employed to address these issues effectively.

IX. LEARNING AND INSIGHTS

The proposed model is able to achieve high accuracy because it uses a state-of-the-art convolutional neural network architecture (EfficientNetB0) and is fine-tuned on a dataset of student images. Fine-tuning allows the model to learn the specific features of student images that are important for classification.

The proposed model can be used to develop real-world applications that can detect student engagement and well-being in classrooms.

X. REAL-WORLD APPLICATIONS

- **Student sleep and stress detection system:** The model could be used to develop a system that alerts teachers when students are sleeping or stressed. This could help teachers to provide better support to their students.
- **Student attendance tracking:** EfficientNet models can be fine-tuned to identify students in classroom images and track their attendance. This information can be used to generate attendance reports for teachers and parents.
- **Student behavior monitoring:** EfficientNet models can be fine-tuned to identify different student behaviors in classroom images, such as talking out of turn, raising their hands, or paying attention. This information can be used to provide feedback to students and teachers, and to identify students who may need additional support.
- **Student learning assessment:** EfficientNet models can be fine-tuned to assess student learning by identifying objects and activities in classroom images. For example, a model could be trained to identify the different types of books that students are reading or the different types of experiments that they are performing. This information can be used to provide teachers with insights into student progress and to develop personalized learning plans.

XI. CONCLUSION

In conclusion, our objective was to create a deep learning model tailored for the classification of students' images into four distinct categories, each representing a different aspect of engagement and well-being within a classroom environment: sleeping on the desk, standing, experiencing stress, and having hands on the desk. To accomplish this, we curated a dataset containing images of ourselves and our fellow students, featuring various poses and expressions.

We fine-tuned this model using our proprietary dataset. Subsequently, we rigorously assessed our model's performance on a held-out test set, benchmarking it against other baseline models for comparative analysis. Our choice of base model, EfficientNet, a cutting-edge convolutional neural network architecture, served as the foundation for our model's development.

Through our evaluation, we also conducted an in-depth examination of the model's predictions, unveiling its strengths and identifying areas where improvements could be made. Our research reflects our commitment to addressing the essential question of assessing student engagement and well-being through image classification, employing state-of-the-art techniques to provide valuable insights and practical applications within the classroom setting.

XII. ACKNOWLEDGMENT

The author would like to express gratitude to the internship mentor for their guidance and support throughout the project.

XIII. INDIVIDUAL CONTRIBUTION

This is compulsory along with snapshot of Gantt Chart

XIV. Implemented/Base Paper

(paper selected to implement your project) Add the paper name, author, conference, Published year

References

[1] H. Kopka and P. W. Daly, *A Guide to LaTeX*, 3rd ed. Harlow, England: Addison-Wesley, 1999.