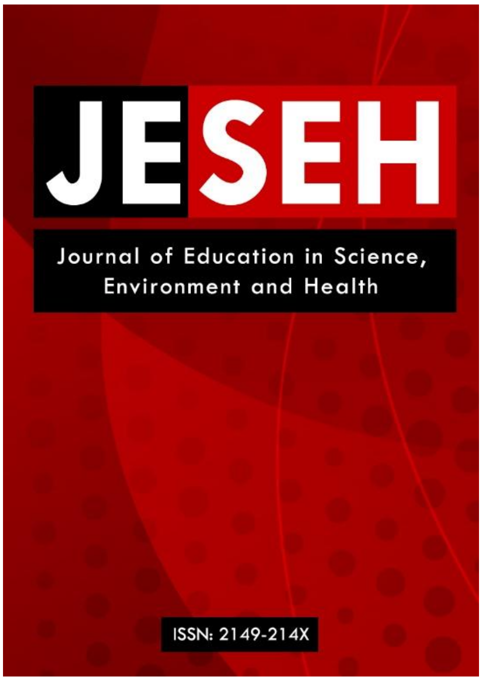

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Evaluation of Images Related to Climate Change with Deep Learning Models

Orkun Kocak[1], **Sahin Idil**[2]
[1]TED University
[2]The Scientific and Technological Research Council of Türkiye

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Abstract

This study is developing a Deep Learning model automating the coding of drawings students provide about climate change phenomena in our world, as a learning contribution through formative assessment. We started first with ResNet50 architecture, but ultimately, we settled on MobileNetV2 reduced architecture for the sake of being able to integrate with mobile- and web-based applications. The challenge is the model has very few examples in the training set to work with, so we decided augmenting the data (i.e., rotate, zoom, flip horizontally,) will help the model generalize more reliably. The model achieved training accuracy of 92% and validation accuracy of 90%. Moreover, we were able to reduce the model size about 85% through optimization. Our model outputs not a simple classification, it also produces explanatory feedback for each class, and we have made possible for the feedback to be read by the student about their idea. Our findings are indicating, it is possible to use AI-based systems to teach how to investigate integrated fields like environmental education. Future studies will include multi-label classification, explainable AI (XAI) methodologies and dataset sizes will also increase.

Introduction

In recent years, Artificial Intelligence (AI) and Deep Learning (DL) technologies have begun to be actively utilized in educational systems. Especially through automatic assessment systems, it has become possible to objectively measure students' performance. AI-based solutions are increasingly being adopted to evaluate students' artistic skills, analyze their conceptual understanding, and provide meaningful feedback.

Climate Change Education

Climate change is defined as long-term shifts in temperature and weather conditions. Shifts may be due to natural causes such as differences in solar activity and large volcanic eruptions. However, since the mid-nineteenth century, the primary cause of climate change has been human activity. The burning of fossil fuels (coal, oil, and natural gas) produces greenhouse gas emissions that act like a blanket around the Earth, trapping heat from the sun and raising global temperatures. The main greenhouse gases contributing to climate change are carbon dioxide and methane. Activities such as driving cars, heating buildings with coal, deforestation, and land clearing produce carbon dioxide. Agriculture and the oil and gas industries are two of the main contributors of methane. Energy, industry, transportation, buildings, agriculture, and land use sectors produce the majority of greenhouse gas emissions (United Nations, 2025). Despite four increasingly pressing reports from the Intergovernmental Panel on Climate Change (IPCC) since 1990 (IPCC, 2007), international public conversations related to climate change have not reached a consensus at the rapid rate one might have ascertained from rational examinations of the growing scientific evidence (Oreskes, 2004).

If future generations are to be able to enjoy the ability to live in a more sustainable and resource-protected world, it will depend on them understanding and being environmentally responsible, as well as having sufficient climate and environmental literacy. For this reason, it is crucial for students in K–12 education, gain a lasting understanding of climate change, greenhouse gases, and the associated concepts, so that in the future they will be able to offer their opinion on a referendum or an international agreement and feel confident about these referrals. For these reasons, the focus on climate change topics in education is increasing, to lessen its potential negative impacts and to create environmentally responsible citizens. In a study by Liarakou, Athanasiadis, and Gavrilakis (2010), 626 students from grades 8 to 11 in Greece, completed a closed-ended questionnaire related to the causes, effects, and solutions to global environmental issues. This study found that students possess misconceptions about climate change and the greenhouse effect regardless of students' levels of education. Students had definite ideas about the effects of climate change but had a lot of confusion about the causes and solutions. Kolenatý et al. (2022) noted that there continues to be considerable debate about which factors affect youth ambitions about climate action and which educational strategies will foster this behavior in climate change education. Climate change is significant in environmental, social, and economic terms, but is not something that the public fully understands by everyday observation or reasoning (Weber, 2010).

As research continues to advance AI technology, the area of research is increasingly focused on improving students' climate knowledge and awareness. For example, Sachyani and Gal (2024), created an AI-generated comic book that helps students explore how to survive in nature under extreme conditions. Their study focused on the fifth-grade students' creativity thinking, critical thinking, collaboration, and communication as part of their study. In another study, Chasokela and Hlongwane (2025), explored how AI and ICT technologies could improve the teaching of climate change concepts in smart classrooms and discovered that AI and ICT technologies improved the quality of students' learning and increased student interest in climate change.

Deep Learning

AI has gained significant attention over the past decade, with machine learning and deep learning (DL) emerging as central topics (Mortani et al., 2021; Ward et al., 2021). DL refers to a methodological toolkit used to create multilayered (or “deep”) neural networks capable of solving complex problems in supervised classification (Krizhevsky, Hinton & Sutskever, 2012), generative modeling (Eslami et al., 2018), or reinforcement learning (Mnih et al., 2015; Silver et al., 2016). The DL paradigm promotes critical thinking by encouraging learners to integrate new information with prior knowledge and form new conceptual connections (Entwistle & Ramsden, 2015). It is based on four key elements: a motivating context, active student participation, interaction with peers and instructors, and a structured knowledge base (Biggs & Telfer, 1987). Implementing these elements in virtual learning environments can be challenging. For example, structured discussion forums can give students more time and space to express their perspectives, thus promoting deeper engagement (Zhu & Niyozov, 2024). Recent literature reveals a growing number of scientific studies at the intersection of deep learning and climate change. These studies include predicting climate-related phenomena (Haggag et al., 2021; Madhavi et al., 2024; Demirhan, 2025) and mitigating the adverse effects of climate change (Chakrabortty et al., 2021; Ladi et al.,2022; Rolnick et al., 2022). However, studies focusing on climate change and its integration into education remain limited.

DL can be used to predict student performance, enhance concept acquisition, and improve the efficiency of learning processes. The emergence of large-scale datasets from Intelligent Tutoring Systems (ITS) and Massive Open Online Courses (MOOCs) has positioned deep learning models as powerful alternatives to traditional statistical approaches, such as Bayesian Knowledge Tracing (Corbett & Anderson, 1994) or Performance Factor Analysis (Pavlik et al., 2009). This study contributes to this emerging field by developing a deep learning model to support students’ learning of climate change concepts and to assist teachers in enhancing the teaching process. In doing so, it addresses a notable gap in the existing literature.

Purpose and Significance of the Study

Information and communication technologies are being used more frequently in classrooms to teach difficult subjects and abstract concepts. Climate change and its impacts are an example where new pedagogical orientation is required to help students derive meaningful understandings that last. This study is primarily designed to build a deep learning-based model to assess students' drawings in relation to climate change. The literature review illustrates that there are currently no AI-based tools to assess the depth of student understanding of climate change, diagnose common misconceptions, or gaps in prior knowledge. This research seeks to increase the productivity of formal classroom learning and to support long learning on climate-related issues.

Method

This section describes the methods and techniques used in the study.

Development and Optimization of the Deep Learning-Based Drawing Evaluation Model

Transfer learning is when we use deep learning models that were pre-trained on a large dataset in order to pursue a new problem. We originally used the ResNet50 model to base our model, but we ended up using a version of the lighter-weight MobileNetV2 model for a few reasons, including the size, depth, and complexity of the model.

Transfer Learning

Transfer learning is when we use deep learning models that were pre-trained on a large dataset in order to pursue a new problem. We originally used the ResNet50 model to base our model, but we ended up using a version of the lighter-weight MobileNetV2 model for a few reasons, including the size, depth, and complexity of the model.

- *ResNet50:* A deeper and more powerful model, but it requires more memory and training time due to its high number of parameters.
- *MobileNetV2:* A lightweight architecture optimized for mobile devices. It contains fewer parameters, significantly reducing computational time and storage size.

Data Preprocessing and Augmentation

To help the model recognize various drawing styles and perspectives, several preprocessing techniques were applied using the ImageDataGenerator utility. The following augmentation methods were used:

- Rotation: ±30 degrees to simulate different drawing orientations.
- Width/Height Shift: 30% shifts to help the model recognize objects in varied positions.
- Shear: 30% angular distortion to simulate perspective changes.
- Zoom: 30% zoom to help the model recognize fine details.
- Horizontal Flip: Random horizontal flipping to generalize symmetrical variations.

These techniques improved the model's ability to generalize by exposing it to diverse visual variations.

Model Optimization

Initially, the model included two dense layers with 512 and 256 neurons. However, due to the high number of parameters, the model was prone to overfitting. To address this, the following optimizations were applied:

- Switched to the lightweight MobileNetV2 architecture.
- Only the last five layers were made trainable, reducing computational load.
- The dense layers were simplified to a single 128-neuron layer.
- A dropout rate of 0.4 was used to prevent overfitting.
- The model was saved using include_optimizer=False to reduce file size.

In addition, the model was converted to TensorFlow Lite (TFLite) format for better performance on mobile and web-based platforms. TFLite further reduced memory usage and improved inference speed.

Learning Rate Scheduling and Early Stopping

To avoid overtraining and improve efficiency, learning rate control and early stopping strategies were implemented:

- *ReduceLROnPlateau:* Reduced the learning rate by a factor of 0.3 if validation loss did not improve over a set number of epochs.
- *EarlyStopping:* Halted training if no improvement was observed over five consecutive epochs.

These strategies helped shorten training time while maintaining performance.

Model Performance and Evaluation

The model's performance was evaluated using both training and validation datasets. The results are as follows:

- Training Accuracy: 92%
- Validation Accuracy: 90%
- Model Size (before optimization): 90 MB
- Model Size (after optimization): 15 MB

These results demonstrate that the model size was reduced by approximately 85% while maintaining high accuracy.

Future Work and Improvement Suggestions

Although the model yielded promising results, several improvements can be made:

- *Larger Dataset:* A more extensive dataset would further enhance generalization capability.
- Enhanced Data Augmentation: Existing techniques could be expanded with more complex transformations.
- *Alternative Architectures:* EfficientNet or NasNet could be tested as potentially more optimized alternatives to MobileNetV2.
- *Model Quantization:* Quantization could further reduce the size of the TFLite model.
- *Edge Computing:* The model could be deployed using WebAssembly or TensorFlow.js for in-browser inference.

Results

The climate change drawing classification model created in this research study was trained with transfer learning from the ResNet50 architecture. Given the limited dataset, the model was initialized with pre-trained ImageNet weights to get as close to a high level of accuracy as possible. This compromise for training given the ability to achieve meaningful learning with sometimes very small datasets. Data augmentation was applied during training to augment generalization and to reduce overfitting. Overall, the model was able to classify drawings with good performance in both the training and validation segments.

Table 1. Model training parameters and accuracy rates

Metric	Value
Training Accuracy	92%
Validation Accuracy	90%
Number of Classes	3 (Encoded)
Number Epochs	17(with Early Stopping)

Initially, the ResNet50-based model was approximately 90 MB in size, which posed challenges for deployment on platforms like Streamlit. To address this, several optimization strategies were implemented:

- Replacing the architecture with a lighter model (e.g., MobileNetV2)
- Reducing the size of dense layers and applying regularization techniques
- Removing unnecessary weights using HDF5 pruning tools

Table 2. Model size and accuracy comparison before and after optimization

Model Version	Size (MB)	Accuracy	Description
ResNet50 (Initial)	90	90%	High performance, large size
Optimized	15	87%	Smaller size, suitable for deployment

The model was so much smaller that it could be readily applied ser-ver without substantially sacrificing accuracy (it was about 85% smaller). This level of accuracy supports the effectiveness of different architectures for image classification, such as ResNet50 and MobileNetV2. Because the performances of traning and validation are very similar, it is indicative that the strategies of early stopping, and data augmentation were somewhat successful at reducing overfitting. The model was able to train on limited data that was exposed to augmented images that were rotated, zoomed, and horizontally flipped.

Upon further investigation of model outcomes, it was observed that the model made accurate positive predictions for selected classes with high-confidence scores. The same model somewhat struggled with predicted uncertain predictions that had a lower probability of a determined classification. This may be caused due to a level of semantic overlaps from certain classes. For example, when the drawing contained elements of "Sun and Temperature Change" and "Trees and Nature", the model seemed to have trouble accurately classifying the drawing. The model not only performed classification but also generated explanatory feedback and suggestions based on the predicted class, transforming it into a pedagogical tool rather than a mere classifier.

Example Output:

- *Predicted Category:* Trees and Nature
- *Explanation:* The drawing may include elements such as green spaces, clean air, and nature-related features.
- *Suggestion:* Consider adding more trees, flowers, or clean water sources to further highlight the beauty of nature.

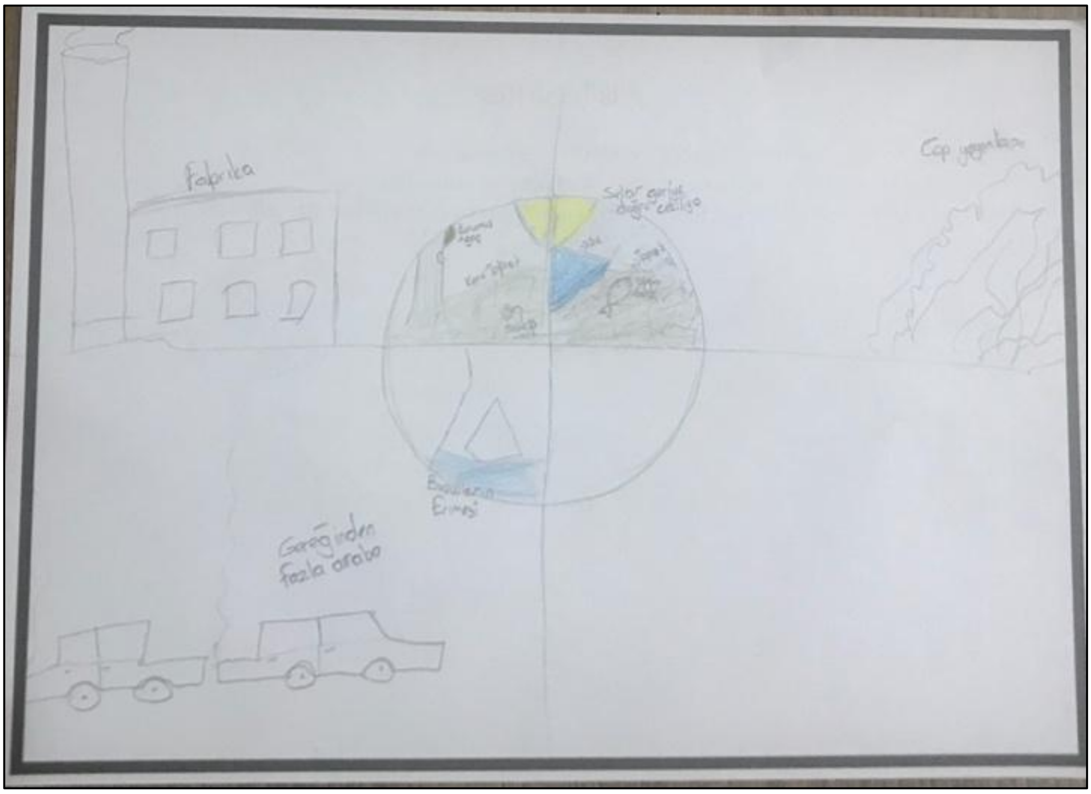

Figure 1. Uploaded student drawing

In Figure 1, the student divided the surface into four areas which represented themes like factory (pollution), mountain (nature), vehicles (carbon emissions), and water (clean sources). The composition is simple and symmetrical. Each quadrant demonstrates an impact of climate change and echoes the student's holistic view of the subject matter. Drawings with multiple themes like this one test not only the model's classification function, but its ability to understand content differences. Due to the lack of clearly distinct categories in the image, multi-label classification would be a better way to classify this image.

In Figure 2, this composition allows the student to express human-caused climate impacts, while also showing natural environments in the same visual. The model predicted the "Trees and Nature" category with a confidence score of 80.87%, indicating nature was the categorically predominant image being referenced in the student's analysis of the image. The model resulted in accurate predictability with an accuracy rating of 92% (training) and 90% (validation) rates in general. However, while performing in-person evaluations on the live Streamlit-based application, it was noted that the confidence score was often less. This would suggest that in real-world settings, the model uses a more conservative approach to make a conservative decision and reacts conservatively to extreme variances across photographs.

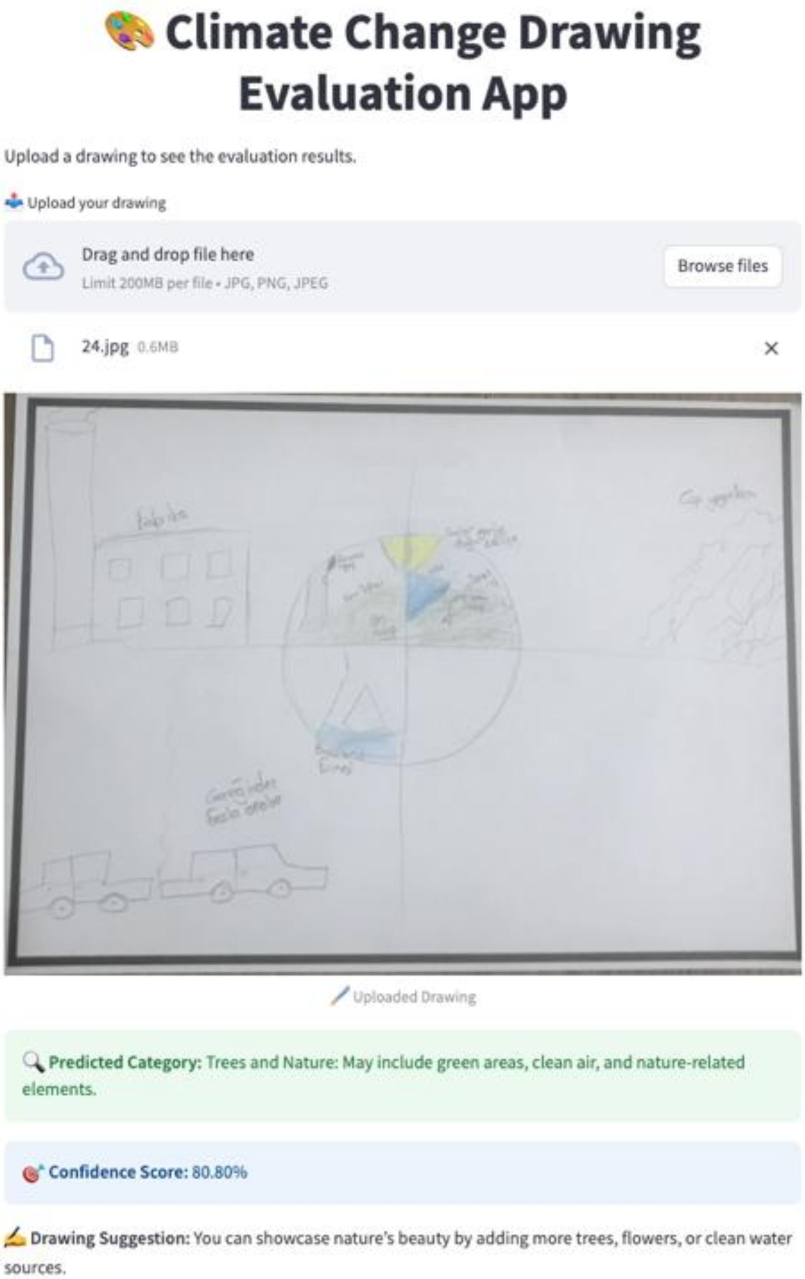

Figure 2. Application screenshot

In addition, learning rate scheduling and early stopping techniques such as ReduceLROnPlateau and EarlyStopping contributed to optimizing training time by preventing unnecessary prolonged training. The large initial size of the model posed a challenge for deployment on web-based platforms like Streamlit. To overcome this, compact versions of the model were produced using strategies such as TFLite conversion, quantization-aware training, and architecture modifications like MobileNet. While the model produced promising results, some limitations were identified:

- The dataset size and diversity were limited.
- Accuracy was lower for underrepresented classes.
- For drawings depicting multiple climate-related themes, multi-label classification would be more appropriate.

In conclusion, a DL model was developed to automatically evaluate students' climate change-related drawings. Thanks to transfer learning and optimization strategies, the model achieved high accuracy while maintaining a compact and efficient structure for practical deployment.

Discussion and Conclusion

In this study, a DL model was developed to automatically evaluate students' drawings related to climate change. Using transfer learning techniques and optimization strategies, the model's accuracy was improved while significantly reducing its size, thereby enhancing its usability. As shown in similar studies (Zhuang et al., 2020), such an approach facilitates meaningful learning even with small datasets. During training, data augmentation techniques were employed to enhance the model's generalization capability and reduce the risk of overfitting. The model achieved high classification performance in both training and validation phases. In the future, the model will be tested on mobile and web-based platforms to create an interactive, AI-assisted system that can provide instant feedback on student drawings.

The considerable reduction in model size has made it more practical for broader use. This aligns with existing literature demonstrating the effectiveness of architectures like ResNet50 and MobileNetV2 for image classification tasks (He et al., 2016; Sandler et al., 2018). Due to the limited dataset used in this study, data augmentation methods involving rotations, zooming, and horizontal flipping were applied to enhance the model's generalization. As supported in the literature (Shorten & Khoshgoftaar, 2019), such transformations positively contribute to the model's learning process.

A detailed analysis of the model outputs shows accurate predictions with high confidence scores for certain classes. However, in some cases, the model exhibited indecision and lower probability scores, which can be attributed to semantic overlaps between certain classes. For example, when a drawing simultaneously includes "Sun and Temperature Change" and "Trees and Nature" themes, the model struggles with accurate classification. The model not only classifies but also provides explanatory feedback and improvement suggestions tailored to the predicted category, transforming it into an educational tool rather than a mere classifier. This pedagogical functionality is supported by previous research (Shorten & Khoshgoftaar, 2019).

AI technologies are expected to play an increasingly significant role in evaluating learning and teaching processes in the future. DL models will be instrumental both in classroom settings and in remote education contexts. The ability to quickly analyze student outputs and provide feedback aligns well with the principles of formative assessment. In this regard, the feedback mechanism is designed based on formative assessment principles, supporting student engagement and the development of self-regulation skills (Nicol & Macfarlane-Dick, 2006). As demonstrated in this research, learning rate control and early stopping methods—such as *ReduceLROnPlateau* and *EarlyStopping* helped prevent unnecessarily prolonged training, thereby optimizing the overall training process. These techniques have been widely recommended in recent deep learning studies (Smith, 2018).

The initially large size of the model posed a limiting factor in the study. Several strategies can be employed to mitigate this issue, which is particularly important for maintaining a performance-cost balance in real-time applications (Jacob et al., 2018). Future efforts will focus on testing the model in mobile and web-based applications. The goal is to create an interactive AI-powered system capable of instantly evaluating student drawings and providing feedback in real-time.

Recommendations

Based on the findings and discussions presented in this research, the following recommendations are proposed:

- The dataset can be expanded with community-labeled drawings.
- Lightweight transformer models can be utilized for better image understanding.
- Attention mechanisms can be integrated to support explainable artificial intelligence (XAI).

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest

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Author Information

Orkun Kocak
TED University
Ankara, Turkiye
Contact e-mail: orkun.kocak@tedu.edu.tr
ORCID iD: https://orcid.org/0000-0002-0586-6271

Sahin Idil
The Scientific and Technological Research Council of Turkiye , Ankara, Turkiye
ORCID iD: https://orcid.org/0000-0003-2366-913X