

Explaining the Black Box: A Study on the Application of Explainable Artificial Intelligence (XAI) Techniques to Machine Learning Models

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Abstract—The increasing reliance on artificial neural networks in various applications has raised concerns about their *black box* nature, making it challenging to understand the decision-making processes behind their predictions. This report addresses this challenge by exploring the application of so-called Explainable Artificial Intelligence (XAI) techniques to machine learning models. Specifically, we employ local explanation approaches, including attributions and counterfactual examples, using the Captum library in the PyTorch such as LIME, saliency maps or Integrated Gradients techniques. Our study aims to shed light on the previously trained models, providing a deeper understanding of how they make predictions and present those findings in this report

I. INTRODUCTION

ARTIFICIAL neural networks (ANNs) have revolutionized various industries and applications, from healthcare to finance, by enabling accurate predictions and decision-making. However, the increasing reliance on these models has also raised concerns about their *black box* nature, making it challenging to understand the decision-making processes behind their predictions. This opacity can lead to a lack of trust in the models, as well as difficulties in identifying biases and errors. To address this challenge, Explainable Artificial Intelligence (XAI) techniques have emerged as a crucial step towards building more transparent and accountable machine learning models. By applying XAI methods, we can gain insights into the internal workings of complex models, providing a deeper understanding of how they make predictions and enabling more informed decision-making. This project aims to explore the application of XAI techniques to machine learning models, specifically focusing on local explanation approaches such as attributions and counterfactual examples. By shedding light on the previously trained models, we aim to provide a better understanding of how they make predictions and contribute to the development of more transparent and trustworthy AI systems.

II. RELATED WORK

During this study, we explored various methods used to enhance the interpretability and transparency of ANNs through XAI techniques. The first paper in this domain we examined was [?] by Ribeiro et al. This paper was the first to publicly introduce the Local Interpretable Model-Agnostic Explanations

(LIME) framework, which generates local, interpretable explanations for the predictions of any machine learning model. The key idea behind LIME is to approximate the original complex model with an interpretable model that is locally faithful to the prediction of interest. This paper was an important step in the development of XAI techniques, as it demonstrated the feasibility and utility of interpretable explanations. Since then, the field of XAI has continued to evolve, with many other techniques (e.g. SHAP, TCAV, GradCAM) being proposed to enhance the transparency and interpretability of AI systems. However, LIME provides local explanations that are specific to individual predictions and while useful, these local explanations may not offer a comprehensive understanding of the model's overall behavior [?].

Different approach for understanding model predictions are saliency maps thoroughly explained by Simonyan et al. [?]. This paper presents the method, which computes the gradient of the score of the predicted class with respect to the input image. The gradient essentially measures how small changes in each pixel value of the image will affect the output score. The absolute values of these gradients are taken to represent the importance of each pixel and pixels with larger gradient magnitudes are considered more important for the classification decision. Therefore, saliency maps effectively highlight discriminative image regions and objects, which are easily interpretable by a human eye. Such examples are shown and prove the usefulness of this method.

To have a broader view and better understanding using another method we reviewed another influential paper by Sundararajan et al. [?], which provided an alternative surrogate-based methods like LIME or sometimes misleading saliency maps [?]. The authors introduce and demonstrate the usefulness of Integrated Gradients through various case studies, including image classification. They show that this method can provide meaningful and intuitive explanations of the model's predictions, which can be valuable for tasks like feature importance analysis. Additionally, the authors compare Integrated Gradients method to other gradient-based attribution methods, such as Saliency Maps and Deconvolution, and highlight the advantages of it in terms of satisfying desirable properties for explanations.

Furthermore, counterfactuals are an essential aspect of XAI, as they provide a way to evaluate the robustness of a model's predictions by considering what would have happened if

certain conditions had been different [?]. This is particularly important in high-stakes applications, such as healthcare or finance, where the consequences of incorrect predictions can be severe. For example, Adebayo et al. [?] evaluated the reliability of saliency maps on the MNIST and CIFAR-10 image classification datasets by applying counterfactual perturbations like rotation and occlusion to the input images. They found that many popular saliency map methods failed to provide faithful explanations, underscoring the importance of using counterfactuals to assess the robustness of model predictions.

Those papers provide a solid ground for experimenting on different models with different methods in order to fully understand models predictions.

III. METHODS

This experiment will be conducted on various types of data and different models. Those models are: MLP models for classifying iris flowers, distinguishing wines and diagnosing breast cancer, MLP models and CNN network for classifying handwritten numbers from the MNIST dataset and lastly CNN network for distinguishing objects in images from the CIFAR10 dataset.

Based on the research, general knowledge, and the types of data and models involved, the experiment will utilize a combination of local and global explanation methods to provide insights into the inner workings of these machine learning systems.

A. Explainable AI Techniques

For local explanations, the following techniques will be employed:

- **LIME:** This method learns an interpretable model around the prediction, allowing for an understanding of the key factors driving the model's output for a specific instance. LIME is a suitable choice as it is a model-agnostic approach that can be applied to a wide range of machine learning models, including the MLP and CNN architectures used in this experiment.
- **Saliency Maps:** Saliency maps highlight the input features that have the most significant influence on the model's prediction for a given instance. This technique is particularly useful for understanding the decision-making process of the CNN models used for image classification tasks, as it can identify the salient regions of the input images that are driving the predictions.
- **Minimal Parameter Perturbation:** This counterfactual explanation method identifies the minimal changes required to the input features to change the model's prediction. By understanding the necessary perturbations, we can gain insights into the model's decision boundaries and the key factors contributing to its predictions.

In addition to these local explanation methods, the experiment will also explore global explanations to understand the overall behavior and assumptions of the trained models.

B. Experiments

IV. RESULTS

Present the results of the local and global explanations. Interpret the findings, discuss their significance, and potential implications.

A. Iris MLP classifier

B. Wine MLP classifier

C. Breast cancer MLP classifier

D. MNIST MLP classifier

- 1) Flatten:
- 2) LBP:
- 3) HOG:

E. MNIST CNN classifier

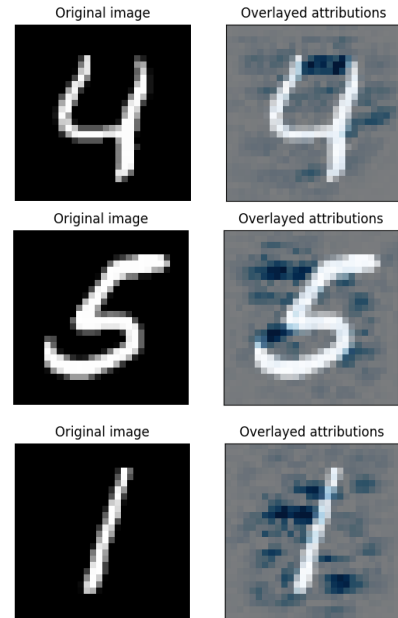


Fig. 1. Saliency maps of chosen MNIST digits

The CNN for recognizing handwritten digits from the MNIST dataset was analyzed using the saliency methods. The resulting saliency maps are visualized on fig. 1. The blue pixels show the areas that most influence the model's predictions.

Unexpectedly, the obtained saliency maps predominantly highlight background pixels adjacent to the digits rather than the digits themselves. One plausible explanation of this phenomenon is that the CNN has learned the absence of pixels in a specific region as important information for its classification decisions — for example, the digits 4 and 5 are characterized by the lack of the closed regions. If one was to add pixels to these areas 4 would turn into a 9, and 5 would turn into a 6. Therefore, these areas are highlighted as important to the classification results, because it is essential that no pixels exist in those areas. Such behaviour might suggest that the model is not recognizing the digits by their shape directly, but rather

by elimination — i.e. an important characteristic of a digit 4 is that it is not a 9.

The background pixels might also provide contextual information about the area around the digit. This is especially important in shape recognition tasks, such as digit recognition. For example, the top bar at the digit 5 is oriented to the right-hand side, however, there are pixels highlighted to the left-hand side. That is because for a line to be considered as oriented to the right, there need to be both a presence of pixels to the right, and a lack of them to the left. Therefore, the background also needs to be considered in order to correctly determine the shape characteristics and boundaries.

Another unfortunate possibility of such behaviour may be some issues with the model. Overfitting could cause the model to focus on some background pixels, that are not really representative of the digit features. However, it should be noted that during the model evaluation, we did not observe a drop in accuracy on the test set during training — a typical sign of overfitting. Additionally, the performance of the model on the testing data was satisfactory, which speaks against the potential issues with the model.

F. CIFAR10 CNN classifier

V. SUMMARY

Summarize the main conclusions and suggest future work.

VI. REFERENCES