

# Allowing humans to interactively guide machines where to look does *not* always improve human-AI team’s classification accuracy

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## Abstract

Via thousands of papers in Explainable AI (XAI), attention maps [50] and feature attribution maps [9] have been established as a common means for finding how important each input feature is to an AI’s decisions. It is an interesting, unexplored question whether allowing users to edit the feature importance at test time would improve a human-AI team’s accuracy on downstream tasks. In this paper, we address this question by leveraging CHM-Corr, a state-of-the-art, ante-hoc explainable classifier [48] that first predicts patch-wise correspondences between the input and training-set images, and then base on them to make classification decisions. We build CHM-Corr++, an interactive interface for CHM-Corr, enabling users to edit the feature attribution map provided by CHM-Corr and observe updated model decisions. Via CHM-Corr++, users can gain insights into if, when, and how the model changes its outputs, improving their understanding beyond static explanations. However, our user study with 18 users who performed 1,400 decisions finds no statistical significance that our interactive approach improves user accuracy on CUB-200 bird image classification over static explanations. This challenges the hypothesis that interactivity can boost human-AI team accuracy [16, 30, 32, 34, 42, 44, 46, 47] and raises needs for future research. We open-source CHM-Corr++, an interactive tool for editing image classifier attention (see an interactive demo [here](#)). We release code and data on [github](#).

## 1. Introduction

Despite much attention from the community, the practical utility of Explainable AI (XAI) tools in downstream applications (e.g., image classification [20, 24, 37, 43]) remains limited, hindering human-AI collaboration in real-world settings. A major **limitation** is that there is no interface for humans to provide feedback to the AI for the model to update its decisions, which could change users’ thoughts

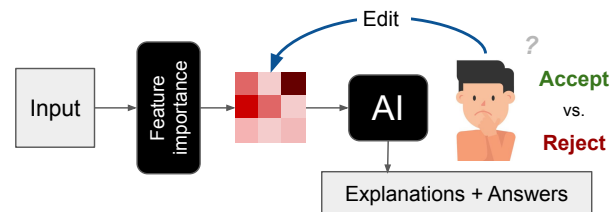


Figure 1. Users provide **feedback** to the explainable AI by editing the feature importance map (like an “attention map” [50]).

and final decisions. For example, feature attribution maps [9, 15] and example-based explanations [37] are among the most popular XAI methods that offer insights into “what a model is looking at” and which real examples support a model decision, respectively. However, they only offer a **static, one-time** explanation of the input. Here, we test allowing users to edit the “attention” input to the model and observe updated model decisions iteratively until they are ready to make decisions (Fig. 1).

We perform our study on CHM-Corr, a recent explainable CUB-200 bird classifier [48] that combines the best of both worlds by first finding, at the patch level, how the input image is similar to the nearest training-set examples, and then using these patch-wise correspondences to predict the image label (see Fig. 2-b and Supp. A3 for examples of CHM-Corr explanations). CHM-Corr explanations enable users to achieve **state-of-the-art human-AI team accuracy** in bird identification on CUB-200 [48].

We build an interactive interface called CHM-Corr++ for CHM-Corr, allowing users to manipulate the “attention” of the CHM-Corr classifier by selecting the set of patches that the classifier uses in decision-making (Fig. 1). By iteratively telling the model where to look, and observing the changes in the output space (see Fig. 2), users could better understand the AI model and make more accurate decisions.

Via a user study of 1400 decisions, surprisingly, we did not find the interactivity to help improve users’ decision-making accuracy (Tab. 1). This finding is intriguing and

in stark contrast to the common hypothesis that interactive explanations might improve human-AI collaboration effectiveness and therefore human-AI team accuracy [30, 34, 42, 44].

## 2. Related Work

Fine-grained visual classification is a domain with active XAI research. Numerous explanations methods have been proposed, producing explanations of various forms. Representative forms include heatmaps [31, 40], examples [21, 38, 48, 49], concepts [26, 41, 54], and prototypes [14, 18, 35]. Regardless of the form, however, most explanations are *static*. They are presented to users in a unidirectional manner without opportunities for follow-up interactions. In this work, we explore *interactive* XAI, following growing calls from the AI and HCI communities [1, 22, 28, 30, 33, 55].

Prior work has demonstrated the needs and benefits of interactive XAI. Notably, Lakkaraju *et al.* [30] found practitioners strongly prefer interactive interfaces when making decisions with AI systems. Hohman *et al.* [22] found that interactivity was fundamental for data scientists in interpreting and comparing AI systems. Kulesza *et al.* [28] found that interactivity increased users’ understanding of the AI system and ability to correct its mistakes.

However, there is a lack of interactive XAI tools that help users gain a better understanding of *computer vision* models through direct interaction with the models. Many existing tools are proprietary (e.g., AIFinnity [12], Symphony [10]), not applicable to computer vision models (e.g., Gamut [22], EluciDebug [28], TalkToModel [45], AVTALER [56]), or support different functionalities (e.g., Shared Interest [11], ActiVis [23], CNN Explainer [53]). In contrast, our interactive tool, CHM-Corr++, enable users to directly control an image classification model’s attention to particular regions of the input and observe changes to its outputs (see Fig. 2). We expect CHM-Corr++ to help users build an understanding of if, when, and how the model changes its outputs, on top of the understanding provided by static explanations.

Finally, our work builds on and contributes to research on human-AI collaboration [5–8, 13, 27, 29, 36, 39, 52] that explores how humans work together with AI systems to achieve shared goals. Particularly relevant is work that studied explanations’ role in human-AI decision making, especially in the context of fine-grained visual recognition [17, 24, 25, 37, 38, 48]. However, most if not all explanations studied in prior work are *static*. In this work, we further the field’s understanding by exploring the role of *dynamic* explanations in human-AI collaboration.

## 3. Method

### 3.1. CHM-Corr++: An interactive interface for controlling model attention

For interactive human-AI collaboration, we developed an interactive interface that enables users to control model attention. Our interface is built on CHM-Corr [48], a visual correspondence-based image classification model that produces *static* explanations of its outputs. Given an input image, CHM-Corr employs a kNN approach to extract the  $N = 50$  most similar candidate images from the training set. It then divides the input image into  $7 \times 7$  non-overlapping patches and compares them with corresponding patches in each candidate image. Based on the cosine similarity among patches, CHM-Corr makes the prediction.

However, CHM-Corr is completely automatic and sometimes focuses on image patches that are not semantically meaningful to users (e.g., background or indiscriminative features – Figs. A1a & A3a). Therefore, we built an interactive interface named CHM-Corr++ that enables users to select image patches that the model should focus on, or in other words, control the model’s attention. At a high level, users are presented with the new attention, support samples, and model outputs. The interface was developed using Python and Gradio [2]. We utilized Gradio with a custom HTML component that enables users to control model attention in a  $7 \times 7$  grid. Compared with CHM-Corr, CHM-Corr++ enables a more interactive and user-centric image classification process, accompanied by *dynamic* explanations of the model’s outputs.

### 3.2. User study

We next explore the effectiveness of static and dynamic explanations with a user study. Our problem setup is as follows (see Fig. 2): Given an input image (e.g., Cardinal), the model predicts its class (c) and provides an explanation (b) for its prediction. The user’s task is to accept or reject (d) the model’s original prediction (Summer Tanager) based on the provided explanation.

**Static vs. dynamic explanations.** In the *static* explanation setting, the model provides five support samples from the predicted class, along with patch annotations highlighting the most similar corresponding patch pairs between the input and the five support samples (see Fig. A1a).

In the *dynamic* explanation setting, the model provides the same type of explanations. However, users can also control the model’s attention by selecting input image patches the model should focus on. Based on the selections, the model makes a prediction again and produces corresponding explanations (shown in Fig. A1b). Note that the new prediction can be same as the original prediction. This process enables users to explore if, when, and how the model’s prediction changes based on their selections (e.g., users can

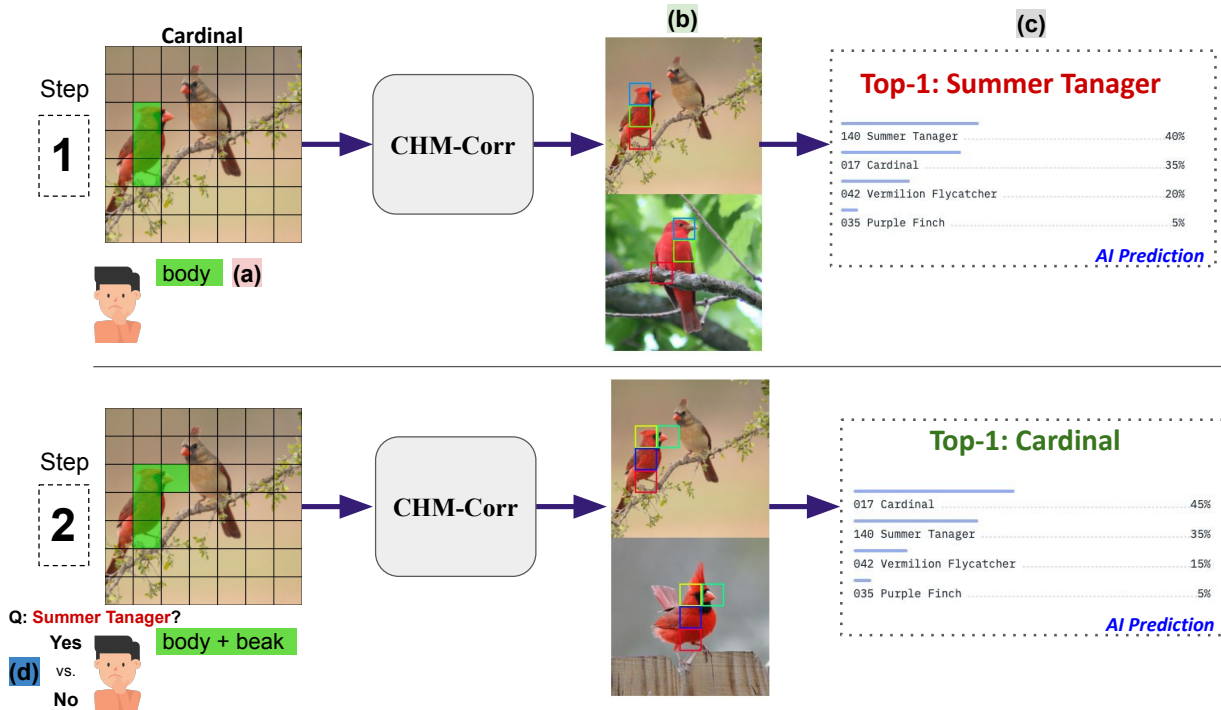


Figure 2. Our CHM-Corr++ interactive interface. We let users interact with the image classification model (here CHM-Corr [48]) via controlling the attention (selecting patches) the model should look at (a). Based on the user-guided attention, the model compares the input image (GT class: Cardinal) with candidate, training examples to simultaneously generate visual-correspondence explanations (b) and predictions (c). The user **iteratively** observes the dynamic explanations (b) and predictions (c) to understand the image classification model to accept or reject (d) the *original* top-1 predicted label (here **Summer Tanager**).

generate counterfactual explanations via observing the answer for “what if?” questions). For example, Fig. 2 demonstrates how the model’s predictions change upon human interaction. Initially, using patches that only includes the bird’s body, the model (CHM-Corr [48]) incorrectly predicts Summer Tanager (Step 1). However, with user-guided attention on patches that include both the body and the beak, the model correctly predicts Cardinal (Step 2).

The key difference between static and dynamic explanations lies in the level of interactivity and user involvement. Static explanations provide a fixed set of supporting information to help users make a decision, while dynamic explanations allow users to actively explore and influence the model’s behavior, leading to a more engaging and informative decision-making process.

**Study materials.** Following prior works [17, 37, 48], we balance the number of correct and incorrect model predictions. From the test set of CUB-200 [51], we select 600 samples, consisting of 300 correctly classified and 300 misclassified by CHM-Corr [48], resulting in a random-chance accuracy of 50% for the task. We input each image to the model to obtain the model’s predictions and explanations.

**Data collection and participants.** Due to the complex-

ity of our interface, we decided to pilot the study with ML experts who are knowledgeable about XAI. We recruited 18 participants, most of whom were Master’s and Ph.D. students in ML. Each participant completed one to several submissions, where each submission consisted of 20 decisions on whether to accept or reject the model’s original prediction (e.g., Summer Tanager in Fig. 2). In total, we collected data on 1400 decisions.

## 4. Results

In our study, participants in the dynamic explanation setting “used” (i.e., controlling the model’s attention and seeing a new prediction) the interactive interface 1.93 times after seeing the model’s original prediction. That is, participants in the dynamic explanation setting saw around  $3 \approx 1$  (original) + 1.93 (new) model predictions on average. In this section, we explore the effect of this interactivity.

### 4.1. Interactivity did not improve decision accuracy

To our surprise, interactivity did not improve participants’ decision accuracy. Dynamic explanations provided little to no benefit over static explanations for participants in assess-

Table 1. User study results. We report per-user mean decision accuracy ( $\mu$ ) and standard deviation ( $\sigma$ ) over a study of 18 machine learning experts who generated in total of 70 submissions (each with 20 decisions).

Explanation type	Static (CHM-Corr)		Dynamic (CHM-Corr++)	
$\mu \pm \sigma$	Overall		Overall	
	72.68 $\pm$ 12.36		73.57 $\pm$ 10.42	
	AI originally correct	AI originally incorrect	AI originally correct	AI originally incorrect
	85.21 $\pm$ 11.82	60.13 $\pm$ 18.66	86.79 $\pm$ 13.16	59.39 $\pm$ 15.51
# of decisions	283	277	443	397
# of submissions	28		42	

ing the correctness of the model’s original prediction. The overall decision accuracy is 72.68% with static and 73.57% with dynamic explanations (Tab. 1). Both are higher than the random-chance accuracy (50%) but still far short of where we want to be (100%). This result suggests that interactivity does not always benefit users, contrary to common belief that interactivity inherently boosts user understanding and task performance [30, 55].

#### 4.2. Participants struggled to reject incorrect model predictions

Next, to understand where participants struggled most, we separately analyze results on instances where the model’s original prediction was correct and instances where it was incorrect (Tab. 1). We find participants’ decision accuracy on correct instances is much higher than that on incorrect ones for both types of explanations: 85.21% vs. 60.13% with static, 86.79% vs. 59.39% with dynamic. This result is consistent with prior findings that users tend to accept AI predictions as correct even when they are incorrect [19, 24, 37, 48], highlighting the need for tools that help users detect and reject AI errors [3, 4].

#### 4.3. The usefulness of interactivity depended on the interaction outcomes

Finally, to better understand the effect of interactivity, we break down participants’ decision accuracy with dynamic explanations based on the interaction outcomes (Tab. 2). Here, “consistent” refers to the model maintaining its original prediction even after the user controlled its attention.

**When the model is originally correct (i, ii)**, we find that participants’ decision accuracy is higher when the model is consistent than not (90.80% vs. 75.21%). This result is in line with our expectations. When the model maintains

Table 2. Participants’ decision accuracy (%) with dynamic explanations under different settings.

AI model correctness w.r.t. human interaction	Acc (%)
(i) Originally correct and consistent (always correct)	90.80
(ii) Originally correct and inconsistent (becomes incorrect)	75.21
(iii) Originally incorrect and consistent (always incorrect)	52.55
(iv) Originally incorrect and inconsistent (always incorrect)	62.11
(v) Originally incorrect and inconsistent (becomes correct)	65.43

its prediction after attention control, participants may gain higher confidence in the prediction and accept it as correct (see Supp. Figs. A1 and A2).

**When the model is originally incorrect (iii, iv, v)**, participants’ decision accuracy is lower when the model is consistent than not (52.55% vs. 62.11  $\rightarrow$  65.43%). Again, this result is as expected. When the model maintains its prediction, even when it is incorrect, participants may gain higher confidence in the prediction and accept the prediction as correct. What happens when the model is inconsistent as shown in Supp. Fig. A4? We find that when the model’s new predictions are always incorrect, participants’ decision accuracy is 62.11%. But when the model eventually becomes correct, participants’ decision accuracy goes up to 65.43%. That is, the interactive interface is most helpful when users’ attention control changes the model’s prediction from incorrect to correct (Supp. Fig. A3). As such, understanding when users can and cannot help the model be more accurate, and aiding users in the process, would be important directions for future research.

## 5. Discussion

We assume two leading hypotheses for why dynamic explanations do not surpass static explanations in improving human decision accuracy. First, regarding the nature of the task, in most instances, AI attention is already sufficient, as the birds are well-centered and clearly visible. Changing the task domain, for example, to include complex scenes where AI struggles to focus on the correct pixels, would likely enhance the effectiveness of CHM-Corr++. Second, we mentioned in Sec. 4.3 that CHM-Corr++ is especially helpful when the base CHM-Corr model can classify correctly. Yet, this base classifier has shortcomings (see Supp. A2) and inherently makes CHM-Corr++ ineffective in many cases (e.g., Supp. Figs. A2 & A4). We hope our open-source tool and investigation of dynamic explanations stimulates further research towards enabling effective human-AI interaction in computer vision.

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