

Human Attention in Fine-grained Classification

Yao Rong¹

yao.rong@uni-tuebingen.de

Wenjia Xu²

xuwenjia16@mails.ucas.ac.cn

Zeynep Akata^{1,3}

zeynep.akata@uni-tuebingen.de

Enkelejda Kasneci¹

enkelejda.kasneci@uni-tuebingen.de

¹ University of Tübingen, Germany

² University of Chinese Academy of Sciences, Beijing, China

³ Max Planck Institute for Intelligent Systems, Tübingen, Germany

Abstract

The way humans attend to, process and classify a given image has the potential to vastly benefit the performance of deep learning models. Exploiting where humans are focusing can rectify models when they are deviating from essential features for correct decisions. To validate that human attention contains valuable information for decision-making processes such as fine-grained classification, we compare human attention and model explanations in discovering important features. Towards this goal, we collect human gaze data for the fine-grained classification dataset CUB and build a dataset named CUB-GHA (Gaze-based Human Attention). Furthermore, we propose the Gaze Augmentation Training (GAT) and Knowledge Fusion Network (KFN) to integrate human gaze knowledge into classification models. We implement our proposals in CUB-GHA and the recently released medical dataset CXR-Eye of chest X-ray images, which includes gaze data collected from a radiologist. Our result reveals that integrating human attention knowledge benefits classification effectively, e.g. improving the baseline by 4.38% on CXR. Hence, our work provides not only valuable insights into understanding human attention in fine-grained classification, but also contributes to future research in integrating human gaze with computer vision tasks. CUB-GHA and code are available at <https://github.com/yaorong0921/CUB-GHA>.

1 Introduction

Through a lifelong learning process, humans have developed a selective attentional mechanism, which has received attention in many areas of artificial intelligence [52]. As human attention can be revealed from gaze data, it bears the potential to explain our behavior and decisions [51]. Many computer vision applications embrace human gaze information to detect salient objects for solving tasks [19, 52, 39]. To visually illustrate human attention in these tasks, it is common to add a Gaussian filter on fixation points to form a feature map [15], which is also called *saliency* map [20] (see Figure 1). Similar to how gaze explains

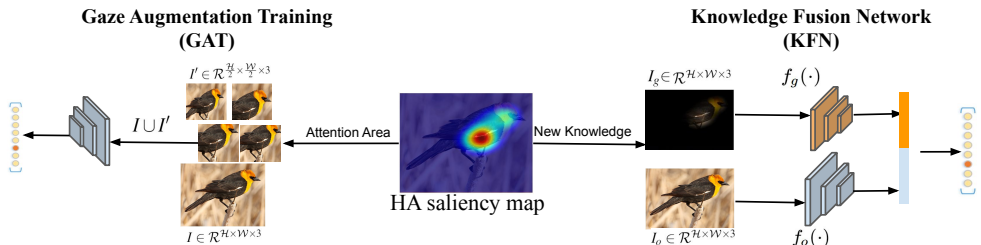


Figure 1: Overview of our proposed methodology. HA saliency map is used to obtain attention area which is used to enhance the training dataset in Gaze Augmentation Training (Left), while it is used as extra knowledge and fused together with the image knowledge in the Knowledge Fusion Network (Right).

human decisions, the post-hoc attention of a network, i.e. model explanation, tries to reveal important regions for neural network decision-making [10, 50, 55, 40, 42, 57]. Both can be visualized by means of saliency maps, thus allowing the study of similarities and differences between them. In this context, several previous works show that humans and models are looking at different regions when performing the same task [4, 56]. However, it is not clear whether a feature discovered by a human is more efficient for solving a given task or not. Our work addresses this research gap and the hypotheses that (1) human attention focuses on essential features for solving the task (e.g. fine-grained classification); (2) using human attention also allows improving model performance in accomplishing the task. To validate the first hypothesis, we first capture and present human attention in the style of a saliency map. We compare the regions that human attention covers with the ones that are discovered by the model (model explanation), and show that human attention hints on the regions that are more discriminative in the classification. We propose two modules which make use of the essential features revealed by human gaze to validate the second hypothesis: we use Gaze Augmentation Training (GAT) to train a better classifier and a Knowledge Fusion Network (KFN) to integrate the human attention knowledge into models.

Our contributions are as follows: (1) We collect human gaze data for the fine-grained data set CUB, enhance it by incorporating human attention and coin this new dataset as **CUB-GHA** (Gazed-based Human Attention). For this novel dataset, we also validate the efficiency of human gaze data in discovering discriminative features. (2) We propose two novel modules to incorporate human attention knowledge in classification tasks: Gaze Augmentation Training (GAT) and Knowledge Fusion Network (KFN). (3) To showcase the relevance of our work for highly relevant applications, we evaluate our methods not only on our novel CUB-GHA dataset, but also on chest radiograph images from a recently released dataset CXR-Eye (which contains also gaze data). Our work shows that human attention knowledge can be successfully integrated in classification models and help improve the model performance with regard to the state-of-the-art in different classification tasks.

2 Related Work

Human Gaze in Machine Learning. Recent developments in hardware devices allow for the precise recording of eye movements in different activities, ranging from human-computer interaction [26, 27] to complex and dynamic real-world tasks, such as driving [4, 47] and robotics [3, 58, 45]. Furthermore, the way that visual information is processed can reveal

information about a person’s strategy or level of expertise [6]. In the medical domain, researchers have validated that gaze data reveals patterns which can benefit AI models, as for disease (Pneumonia and Congestive Heart Failure) classification [18]. In computer vision, gaze data has proven its usefulness in various applications [9, 32, 34, 39]. E.g., [19] collects gaze (coordinates, duration, etc.) vectors for 60 bird classes in dataset [46] to form embeddings for zero-shot learning. [32] compares the attention map generated by an attention module (two convolutional layers) with human attention maps generated by the data from [9] and shows that human attention surpasses the attention module. [34] proposes a photograph cropping system using the collected fixation data to identify important content and compute the best crop. Eye tracking data is also used to extract dominant objects in videos [39]. Different from previous works which use gaze for specific tasks [9, 34, 39], our proposal GAT leverages human attention to train a better backbone which can be used in many different tasks and frameworks. Moreover, we evaluate GAT and KFN for two different classification tasks and thus show the general validity of our methods.

Attention Module in Fine-grained Classification. Many previous works [10, 12, 22, 23, 24, 37, 41, 51, 53, 56, 58] integrate attention modules in networks to localize the parts which are important for fine-grained classifications and make use of the information of the discriminative parts to improve the models’ performance. [10, 22, 23, 24, 37] adopt the Recurrent Attention Model (RAM) [28], where an attention agent is deployed to predict locations of the discriminative regions, and train the classifier based on these cropped regions. The attention agent is trained with a reinforcement learning algorithm to address the non-differentiability due to the cropping operation. However, the architecture of this attention model is cumbersome with high computational cost. [12, 41, 51, 53, 56, 58], on the other hand, design attention modules using the output from intermediate layers in networks and enforce it to capture discriminative features. Compared to previous works, we do not use the intermediate outputs from networks to generate model attention but use human attention maps. Our method augments the training set with regions cropped according to human attention and thus accomplishes training a better classifier. We compare our method with previous works and demonstrate the profit of exploiting human attention in Section 5.

3 CUB-GHA Dataset

In this section, we first provide the details of our gaze data collection paradigm and then analyze the effect of machine explanation and human attention to the fine-grained classification model. To collect gaze data, we employ the CUB-200-2011 (CUB) [44] dataset with 11,788 images from 200 bird classes incorporating various annotations: image-level attributes, body part locations, and text descriptions of the bird. Our annotation leads to a human-gaze enhanced version, i.e. CUB-GHA.

We choose the fine-grained CUB dataset for two reasons: 1) The difference between two similar classes lies in local and compositional attributes, which can be precisely captured by human gaze. For instance, it is challenging to achieve a measure for unified human attention when comparing a bear and a horse as there are many differences between them. In contrast, distinguishing between two similar birds with different throat colors presents a more unified problem (as shown in Figure 2). 2) The CUB dataset is widely used for various computer vision tasks, such as fine-grained classification [9, 10, 56], zero-shot learning [1, 28, 49, 53], explainable artificial intelligence [2, 6, 16], etc. Thus, our CUB-GHA may serve as a valuable foundation for exploring the effect of human attention on those tasks.

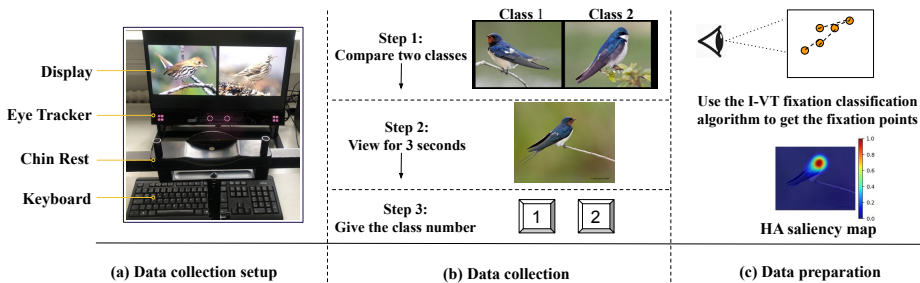


Figure 2: (a) Eye tracker set-up: We use a Tobii Spectrum eye-tracker to capture gaze information at a high frequency of 1200 Hz. (b) Data collection: Step 1 represents a schematic overview of the image comparison task where two images of different species are freely viewed. In Step 2, a randomly selected example of one of the species is shown to the user for which gaze data is then collected. To gamify this setting, the user is asked to choose the correct class in Step 3. (c) Preparing human attention data: we visualize human attention in Gaussian-based saliency maps.

3.1 Gaze Data Collection

Collection Framework. As illustrated in [19], humans fixate on class-discriminative features when they observe two very similar classes. In this paper, we adopt an image comparison game [19], where we encourage participants to look at the discriminative features when comparing two similar images from different categories. The comparison task is designed to be challenging to provide more powerful insights, i.e. two classes in one comparison pair are chosen to be very similar.

A schematic overview of our data collection is presented in Figure 2. Figure 2 (a) shows the experimental setup including a picture of the eye-tracker (Tobii Spectrum Eye Tracker, sampling at 1200 Hz) and the chin rest as well as the display (1920×1080 resolution). The chin rest is used to ensure precise recordings of the eye movements. Each image is re-scaled to fit to the screen and placed at the center. The average distance between the participant’s nose and the screen is approximately 60 cm. The comparison task consists of three steps shown in Figure 2 (b). In step 1, we present two representative images at the same time, each from one bird class of the CUB dataset, e.g. representative images of Barn Swallow and Tree Swallow. We choose the comparison pairs under the same sub-classes, and then different persons manually check the visual similarity to make sure that the comparison is not too simple. The participants are allowed to observe the images for as long as they want. When the participant is ready for the classification task, in step 2, an image from one of the two classes of the CUB dataset is shown. The participant has to choose which category the image belongs to by viewing the image. Note that the image shown for classification is displayed for only 3 seconds to avoid explorative gaze behavior unrelated to the task. One collection session includes one image from each class, meaning that there are 200 images reviewed per session. Every image in CUB is reviewed by five different participants. 25 subjects (19 males and 6 females with mean age 27.64 ± 4.15) participate in the experiment. Although the participants do not take part in the same number of sessions and instances, we make sure that every participant views all classes in every session. It is worth noting that all participants are domain novices with no specific knowledge about birds.

Gaze Data Preparation. The raw gaze data is preprocessed to extract fixation locations using the Velocity-Threshold Identification (I-VT) algorithm [29]. The resulting fixation points offered in the dataset include coordinates and duration information. Based on this

information, we generate saliency maps for human gaze as shown in Figure 2 (c). Every fixation location is modelled as a Gaussian distribution $G(\mu, \sigma^2)$, where σ is 75 pixels (in the display resolution), according to the ratio of the distance to the screen and the approximate foveal area of 2° . The duration of the fixation is then used as a weight for its Gaussian distribution. Finally, the saliency map is presented in grayscale image form. From here on, we note the human attention saliency map generated from gaze data as HA.

3.2 Gaze Data Analysis

In this section, we validate the hypothesis that *HA covers discriminative regions for the fine-grained classification*. Given the same image and the same (visual) task, HA and model explanation (ME) reveal regions which are important in making decisions for humans and models, respectively. Thus, we compare HA with four MEs provided by a trained classifier (vanilla ResNet-50 [14]) with a classification score of 85.58% on CUB, and validate that HA is able to discover features that better differentiate the bird from other bird classes. The four ME used are Class Activations Maps (CAM) [57], Gradient-based CAM (Grad-CAM) [65], InputXGradient (IxG) [40], and IntegratedGradients (IG) [42].

For quantitative comparison, we compare HA and ME using the keep and re-train (KAR) procedure (proposed in the appendix to [12]) to validate if the important regions highlighted by HA and ME help the model to make decisions. Concretely, we gradually insert important pixels to a blank image according to their values in HA or ME saliency maps. The modified percentage of pixels is [5,10,15,20,25,30,50,70,90]. After a certain amount of pixels are inserted, we re-train a new model using the modified train images and report the accuracy on modified test sets. Modified images at 5%, 20% and 70% of pixels inserted using Grad-CAM are shown in Figure 3 (middle). The intuition behind this is that the class-discriminative information should be included in the pixels that are evaluated as very important; with more pixels inserted which are relatively less important, the model performance will not improve much. If a saliency map selects the informative features as being the important ones for classification, the increase of accuracy at the beginning of insertion is rapid, i.e. the resulting higher Area Under the Curve (AUC) indicates a better feature importance estimate.

The keep and retrain curves and the AUC scores for each method are shown in Figure 3 (top), and the qualitative saliency maps for HA and four MEs for one image are shown in the bottom. We see that HA and MEs do not focus on the same image regions: humans consider the white feathers on the black wing as a more important feature, while the model uses the

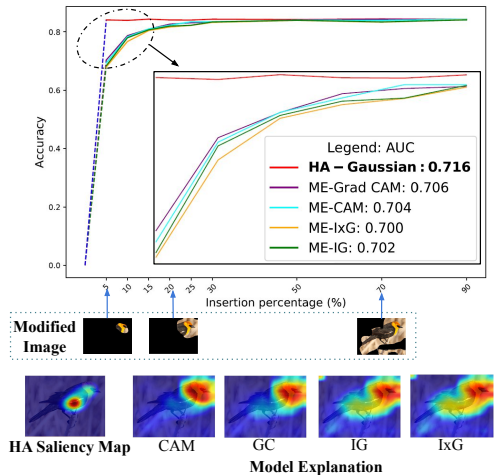


Figure 3: Comparison of HA and ME in discriminative feature discovery. **Top:** Test accuracy on modified datasets using different saliency maps. The x-axis is the insertion percentage and the y-axis is the accuracy on test set. The AUC of each curve is reported in zoom-in image. **Middle:** modified images (using Grad-CAM as an example). **Bottom:** Illustration of HA and four MEs.

yellow head as the most important feature (see the original image in Figure 1). HA discovers more informative and important features for the fine-grained classification model than the MEs do, e.g. HA obtains an AUC score of 0.716 compared to Grad-CAM (0.706) and IG (0.702). With only 5% important pixels revealed, the model trained with HA modified images can reach an accuracy of 81% while the model trained with ME modified images only reaches an accuracy of around 70%. More details of the analyses can be found in the supplementary material.

4 Methodology

In this section, we introduce how we incorporate the gaze information to improve the classification performance, i.e. using gaze to augment training data (GAT) or as an extra information source (KFN). The illustration of the architecture is shown in Figure 1.

4.1 Gaze Augmentation Training

Motivated by the assumption that the model should pay attention to the discriminative image regions (highlighted by HA), we enhance our model’s reaction to those regions by adding them as augmentation in training as illustrated in Figure 1 (left).

To get the k augmentation images for the input image $I \in \mathcal{R}^{\mathcal{H} \times \mathcal{W} \times 3}$ (where \mathcal{H} and \mathcal{W} represent the width and height of the input image), we implement a sliding window algorithm to find areas which contain human attention. A window with the size of (w, h) slides on the HA map $A \in \mathcal{R}^{\mathcal{H} \times \mathcal{W} \times 1}$ from the upper left to the right bottom corner (with stride size s in both dimensions). We rank all the window areas according to the averaged pixel values inside windows and get k cropped images according to top- k highest scores. We resize the cropped images to the half of the width and height of the I , i.e. $I' \in \mathcal{R}^{\frac{\mathcal{H}}{2} \times \frac{\mathcal{W}}{2} \times 3}$, as suggested in [10, 67, 65] where the attended regions are resized into smaller sizes. I' has the same label y as I does. To get various regions, we use various window sizes and the non-maximum suppression. The training set is extended to $I \cup I'$. We train the model on the enlarged dataset with cross-entropy loss. Note that GAT just needs human gaze information in training and the model takes only original images as inputs in the test phase.

4.2 Knowledge Fusion Network

As shown in Fig. 1 (right), our KFN is a two-branch network that fuses the knowledge from HA and the original image features together. The first branch is the image knowledge branch. This branch takes the original images $I_o \in \mathcal{R}^{\mathcal{H} \times \mathcal{W} \times 3}$ as the input, where \mathcal{H} and \mathcal{W} represent the width and height of the input image, respectively. We use a CNN backbone $f_o(\cdot)$ to extract image feature $f_o(I_o) \in \mathcal{R}^{D_o}$ from I_o , where D_o denotes the dimension of the feature channel. Another branch, the HA knowledge branch, incorporates the gaze features of this image. We multiply the gaze information (HA) with the input image by $I_g = I_o \odot A$, where $A \in \mathcal{R}^{\mathcal{H} \times \mathcal{W} \times 1}$ is the HA saliency map. Through this operation, pixels in the image get different weights from the gaze: the area where humans pay attention to is brighter than the rest. I_g contains visual features which are important for the classification. Another CNN backbone $f_g(\cdot)$ is utilized to extract the gaze feature as $f_g(I_g) \in \mathcal{R}^{D_g}$. Then the gaze feature and original image feature are concatenated together to form the fused feature $f(I_o, I_g) \in \mathcal{R}^{(D_o + D_g)}$. In this way, we integrate HA into a multiclass classification task to study the

potential of HA to improve the performance of the image classifier. The whole network is trained with cross-entropy loss.

5 Experiment

In this section, we first introduce datasets and implementation details. Then we show the results of our proposed GAT and KFN. To show the general validity of our methods, We test on two datasets: CUB-GHA and Eye Gaze Data for Chest X-rays (CXR-Eye) [17].

5.1 Datasets and implementation details

CUB-GHA includes 11788 images in total, with 5994 images for training and 5794 for validation [17]. Each image contains eye gaze data from 5 participants. CXR-Eye includes 1083 chest X-ray images with gaze data from a radiologist while performing routine radiology readings [17]. The goal of this dataset is to make a prediction based on the chest X-ray image, whether the subject has one of two clinically prevalent diseases (pneumonia or congestive heart failure (CHF)), or the subject is healthy (normal). The human gaze data is also visualized in the saliency map style. Each image is annotated with one label out of three classes. We choose this dataset because it is a unique human gaze dataset in the medical domain. For such safety-critical applications (e.g. computer-aided diagnosis), we believe the integration of human attention can increase the acceptance and trust of these applications among users.

In our experiments on the CUB dataset, the input images are resized to 448×448 (the images are cropped to this size with the smaller edge first resized to 448) and then randomly flipped horizontally in training. We use the SGD optimizer [43] with an initial learning rate of 0.001. In the experiments on the CXR dataset, the input images are resized to 224×224 and a random horizontal flip is used in training. We use the Adam optimizer [20] with an initial learning rate of 0.0005. Since the CXR-Eye dataset is relatively small, we run 5-fold cross validation and report the average accuracy of the five validation sets as the final score. All experiments are run for totally 100 epochs training on a single NVIDIA GeForce RTX 3090 and the learning rate decreases after every 50 epochs by a factor of 0.1.

For GAT and KFN, we use ResNet-50 [14] and EfficientNet-b5 [43] pretrained on ImageNet as backbones on CUB and CXR, respectively. In GAT, we crop the original image using three sets (large, medium and small) of window sizes (more details can be found in the supplementary material). Inside each set of window sizes, we run a sliding window algorithm and get k augmentation images for each image in the training set. Concretely, k is set to 2 for large, 3 for medium and 4 for small scale, which results in 9 augmentation images in total. When combining GAT and KFN, we use the GAT trained classifier as backbone in our KFN and fine-tune the KFN for only 20 epochs.

5.2 Evaluation on CUB-GHA

Ablation study. To measure the influence of GAT and KFN on the fine-grained classification, we design an ablation study on the CUB dataset where we train a ResNet-50 with cross-entropy loss as the baseline, and several variants by adding GAT and KFN training modules to the baseline. From the results shown in Table 1, we observe that both GAT and KFN can improve the fine-grained classification accuracy by a large margin. GAT (with

HA) improves the baseline model by 2.42% to 88%, which indicates that human gaze falls on areas containing discriminative features for classification. When using HA in KFN, the accuracy score is increased from 85.58% to 86.99%, which demonstrates that KFN integrates the knowledge of human attention successfully. To show the effectiveness and uniqueness of HA knowledge, we use two machine explanation methods Grad-CAM [65] and IG [42] as the saliency maps, replacing HA in GAT and KFN. HA surpasses both methods in the GAT and KFN modules, e.g. KFN (HA) gains 86.99% while KFN (IG) gains 85.66%. It indicates that human gaze contains unique knowledge that can not be acquired by the model itself. From the result of GAT+KFN, we observe that the combination of both exceeds using any of them alone.

| Method | | Acc. |
|----------------|---------------|--------------|
| ResNet-50 [40] | | 85.58 |
| GAT | Grad-CAM [65] | 87.68 |
| | IG [42] | 87.73 |
| | HA | 88.00 |
| KFN | Grad-CAM [65] | 85.04 |
| | IG [42] | 85.66 |
| | HA | 86.99 |
| GAT+KFN | HA | 88.66 |

Table 1: Ablations study of GAT and KFN on CUB. “Acc.” denotes the accuracy in %.

| Method | Acc. |
|----------------|--------------|
| MixUp [52] | 86.23 |
| CutMix [60] | 86.15 |
| SnapMix [43] | 87.75 |
| Ours (GAT) | 88.00 |
| OSME+MAMC [44] | 86.30 |
| TASN [56] | 87.90 |
| API [58] | 87.70 |
| ACNet [42] | 88.10 |
| Ours (KFN+GAT) | 88.66 |

Table 2: Comparison with the state-of-the-art methods on CUB. **Top:** Comparison of GAT with data augmentation methods. **Bottom:** Comparison of GAT+KFN with attention-based models.

Comparison with state-of-the-art. We compare our proposed modules with several state-of-the-art methods. Note that for a fair comparison, we compare with the results of using ResNet-50 as the backbone and the input resolution of 448×448 . First, we compare our GAT with other data augmentation methods, i.e., MixUp [52], CutMix [60] and SnapMix [43] in Table 2 (top). The difference between our GAT and other data augmentation methods is that we do not generate synthetic images. MixUp combines two images and their labels linearly, while the rest replace one part of the image with one part from other images. Our GAT simply extends the dataset with the cropped images, which introduces very low computation cost to train the classifier. Among all these works, training a ResNet-50 with GAT outperforms with other state-of-the-art augmentation methods and achieves an accuracy of 88%. Moreover, this better trained backbone can be combined easily with other framework to further improve the performance, for instance we combine it with our KFN and thus get better results.

We compare our full network with the attention-based methods on CUB in Table 2 (bottom). We choose these methods (OSME+MAMC [44], TASN [56], API [58] and ACNet [42]) due to their high performance and relevance in simulating human attention by attention modules. They apply attention modules to capture discriminative features from the intermediate output in the network, while we use and integrate the HA directly. For instance, [42, 44] applies several layers on the top of the output of the residual block to obtain the region features; API [58] simulates the comparison behavior of humans as our participants do in the data collection in order to learn discriminative representations. Our full network out-

| Method | S3N [8] | S3N + GAT (Ours) | CrossX [45] | CrossX + GAT (Ours) | MMAL [61] | MMAL + GAT (Ours) |
|----------|---------|------------------|-------------|---------------------|-----------|-------------------|
| Accuracy | 87.95% | 88.91% | 87.70% | 88.51% | 89.25% | 89.53% |

Table 3: Combining our GAT model with the state-of-the-art methods on CUB.

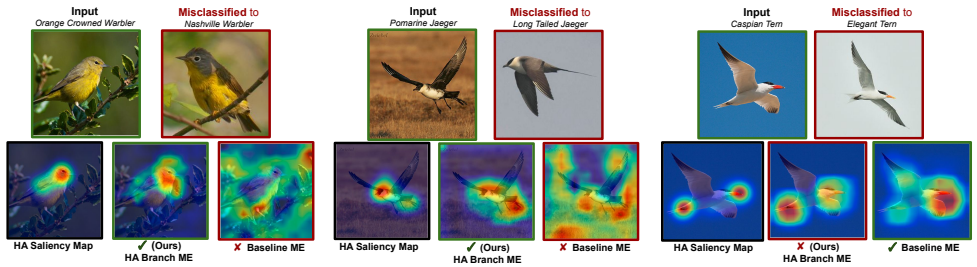


Figure 4: Illustration of model explanations using HA. Two improved examples and one failure example of our model are shown. For each example, we show the input and misclassification classes; HA saliency map, model explanation of our model, and the baseline model.

performs all state-of-the-art models, achieving 88.66% compared to the attention networks API (87.70%) and ACNet (88.10%). The high performance of our KFN and GAT validates that human gaze can benefit a model’s performance in the task.

We combine our module with other state-of-the-art models flexibly and thus improve the performance. In Table 3, we show our re-implementations with official code and our improvement by combining our GAT in S3N [8], CrossX [25] and MMAL [50] models. Please note that no HA information is needed in the inference phase. Our combination of MMAL and GAT improves MMAL from 89.25% to 89.53%. We improve CrossX from 87.70% to 88.51% and S3N from 87.95% to 88.91%, which also surpass the best results given in [8, 25].

Qualitative results. We show two examples from two classes whose accuracy is improved the most compared to the baseline model (vanilla ResNet-50), and one example of a class where our model fails to classify correctly in Figure 4. In the first example, the baseline model looks at the belly of an Orange Crowned Warbler and misclassifies it as a Nashville Warbler who also has a yellow fluffy belly. Our model instead focuses on the throat, which is discriminative between the two classes: an Orange Crowned Warbler has a yellow throat, while a Nashville Warbler has a clear mixture of gray and yellow colors on its throat. In the second example, the discriminative feature is the tail. The baseline model mistakes the background as the tail, while our model localizes the tail successfully. Moreover, our model explanation is also more compact and similar to the human saliency map. In the third example, we show a failure of our model: Our model attends to the feet instead of beak which causes the misclassification of a Caspian Tern as an Elegant Tern. Although our model aligns with the human attention, it puts more weight on the feet of birds, since the color of feet is an important feature for distinguishing between a Caspian Tern and a Common Tern (or an Arctic Tern).

5.3 Evaluation on CXR-Eye

Comparison with state-of-the-art. The state-of-the-art work on CXR-Eye [18] uses the Efficient-b5 [43] as the classifier, however, it deploys random splits to create training, validation and test sets. For a fair comparison, we re-run its network using our 5-fold cross validation setting and report the average of five validation accuracies as the score for this method. The result of this baseline is 70.97%. When implementing GAT, the result is improved to 71.86%; when implementing KFN, the accuracy is improved by 3.45% to 74.42%.

The full model (GAT+KFN) achieves 75.35% exceeding Efficient-b5 [18] by 4.38%. When comparing the performance boost from GAT and KFN, the KFN improves the model on CUB more than GAT. The reason for the difference is how the gaze data is collected.

In CXR-Eye, the gaze data of the radiologist is collected in an interpretation routine. From the examples shown in Figure 5 (sec. column), we see that fixations spread over many locations (light blue area). These locations may play an important role in diagnoses, but GAT localizes the area that the radiologist fixates for relatively longer time. KFN can integrate the knowledge of all potential locations therefore improves the performance by a larger margin.

Qualitative results. To study the influence of integrating HA into the network, we compare the model explanation (Grad-CAM [15]) of each branch in KFN and the qualitative results are shown in Figure 5. From the figure, we see that the HA branch follows more the human attention while the image branch is focusing different areas.

In the first example (top), human attention focuses more on the left side than the right and the HA branch also does, while the image branch looks more on the right side. The image branch in the second example concentrates on a wrong area, but the HA branch corrects the attentive area to the right. Therefore, KFN improves the performance compared to a model only using images. Most importantly, incorporating gaze knowledge helps to increase the trust and acceptance of the model-based decision in applications such as medical diagnostics, since the model aligns with human behavior.

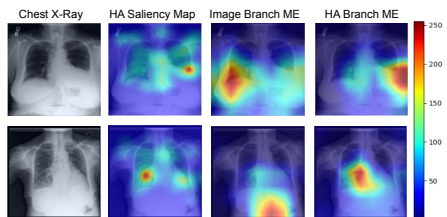


Figure 5: Illustration of the influence of using HA in model explanation. **Left to Right:** the original Chest X-ray image; HA saliency map; Model explanation of the Image Branch (w/o HA knowledge) and Model explanation of the HA Branch.

6 Conclusion

In this work, we investigate human attention in classification tasks on the CUB and CXR datasets. In particular, we collect a new gaze dataset, CUB-GHA, and show that human attention focuses on the discriminative regions for a fine-grained classification task. To study the hypothesis that human attention helps a model in the decision-making, we propose the Gaze Augmentation Training and Knowledge Fusion Network which integrate human attention knowledge into the network. Our proposed method improves the accuracy in classification by a large margin on both datasets, showing the general validity of our methods. Thus, our work indicates that human attention provides hints on distinct features in different classification tasks.

The aim of our work is to demonstrate the potential benefit of human gaze data in classification. As a by-product of this work, we provide the research community with a gaze-enriched dataset CUB-GHA, which can be incorporated with other existing comprehensive annotations (textual explanations, attributes and bounding boxes, etc.). Researchers can therefore validate multiple applications, where human gaze is required in the interaction with a machine.

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