Training De-Confusion: An Interactive, Network-Supported Visual Analysis System for Resolving Errors in Image Classification Training Data

Alex Bäuerle, Heiko Neumann, and Timo Ropinski

Abstract—Convolutional neural networks gain more and more popularity in image classification tasks since they are often even able to outperform human classifiers. While much research has been targeted towards network architecture optimization, the optimization of the labeled training data has not been explicitly targeted yet. Since labeling of training data is time-consuming, it is often performed by less experienced domain experts or even outsourced to online services. Unfortunately, this results in labeling errors, which directly impact the classification performance of the trained network. To overcome this problem, we propose an interactive visual analysis system that helps to spot and correct errors in the training dataset. For this purpose, we have identified instance interpretation errors, class interpretation errors and similarity errors as frequently occurring errors, which shall be resolved to improve classification performance. After we detect these errors, users are guided towards them through a two-step visual analysis process, in which they can directly reassign labels to resolve the detected errors. Thus, with the proposed visual analysis system, the user has to inspect far fewer items to resolve labeling errors in the training dataset, and thus arrives at satisfying training results more quickly.

Index Terms—Convolutional Neural Networks, Training Data, Labeling Errors

1 INTRODUCTION

Since the classification performance of Convolutional Neural Networks (CNN) has greatly improved [19], they are gaining more and more popularity in classification tasks for both research and industrial purposes. To support the development of CNNs, many techniques and visualizations for improving network architectures and hyperparameter tuning exist [21, 40, 45]. Furthermore, visualization techniques have been developed for the communication of classification results as well as for the rationale behind them [10, 29]. While many of these visualizations are helpful in supporting machine learning experts when working with complex network architectures, rather few visualization approaches have been targeted towards laymen using CNNs for their domain tasks.

Besides the network architecture, which in many deep learning frameworks can be chosen from a set of provided networks, the quality and quantity of training and validation data are crucial for a successful training process. However, in many disciplines, it is difficult to obtain large quantities of labeled data with high data quality at a reasonable effort. Researchers for instance, either have to label data themselves, which is a tedious and time-consuming task, or outsource the labeling process to coworkers, students, or paid crowd workers. What all of these labelers have in common is that they do not know the data as well as the domain experts do. This is especially true, when using online services such as Amazon’s Mechanical Turk, where external crowd workers without any domain knowledge label the data [27]. Besides this downside, crowdsourcing is appealing, as it supports the acquisition of large quantities of labeled data. While automatic label assignment can also label large amounts of data with reasonable effort [43], it is also error-prone. When for instance a search term is used as the label for images gathered through a Google image search, there can be images gathered not belonging to the desired class as they are wrongly labeled; and instance interpretation errors, where single images are mislabeled; and similarity errors, where nearly identical images are used in the training dataset. While a detailed explanation of these error types is provided in Sect. 3, Fig. 2 shows error examples as we could detect them with our system in well-known machine learning bench-
we employ interactive high-dimensional embedding techniques. Thus, they are so similar that one might question if they should both be in the dataset. Our contributions are threefold:

- First, we categorize and describe commonly made labeling errors impacting image classification performance.
- Second, we propose how to automatically detect potential candidates for these error types in training datasets by exploiting classification results.
- Third, we suggest interactive visualization techniques to guide the user to these potential errors and to ultimately help to resolve them.

All of these contributions have been integrated into a visual analysis system, which enables domain experts to let non-experts label their data, as for instance through a crowdsourcing interface, while keeping the data quality at a high standard. The pipeline that allows this automatic error correction can be seen in Fig. 1. As a consequence, more training data can be labeled at lower costs and a more reliable outcome at the same time. Since we utilize classification results for detecting potential errors, the user only has to look at as many items as have been misclassified by the system. This means, that for a classifier that reaches an accuracy of 90 percent on a given dataset, only ten percent of the images have to be reviewed at maximum. Since there are no comparable approaches to ours, the user otherwise would have to look over the entire dataset again. Furthermore, in contrast to other approaches tailored towards the improvement of classification results, the presented approach has the benefit, that it does not require extensive experience with machine learning and model optimization, and is thus also applicable by machine learning laymen. Thus, we believe that we make contributions, which qualify this paper as both, a design study and an application paper. For the design study part, we reason about the visualization design underlying our system, while we address a well defined application, i.e., using CNNs for image classification in various domains.

The remainder of this paper is structured as follows. We will first discuss work related to our approach in Sect. 2, before we introduce and discuss the error types in Sect. 3. To clarify what a user does to improve the training data, we define user tasks in Sect. 4. The visualization techniques proposed to identify and resolve these errors are discussed in Sect. 5, while the application of the proposed techniques to three use cases from different domains are discussed in Sect. 6. Following this, we present results of the study we conducted in Sect. 7. Limitations are then noted in Sect. 8. The paper concludes in Sect. 9.

2 Related Work

Since CNNs are often treated as black boxes, many strive to visualize their functionality and thus give insight into how and why they work. While Endert et al. review many approaches integrating visual analytics and machine learning [12], we solely present work targeted towards the improvement of classifiers in general. We differentiate between visualizations that give insight into different aspects of classification through deep learning, and explain how our approach delineates from the existing body of related work.

Architecture Visualization. There are many tools for visualizing network architectures [21, 38, 40, 45]. They help to understand the model used to train a classifier and are important for network improvement. However, since we do not aim for architecture optimization which can only be done with appropriate knowledge about neural network modeling and is beyond the possibilities of a layman user, we will not discuss these techniques in detail.

Activation Visualization. Visualizing activations of individual network layers has been addressed by many researchers to gain insight into how the network obtains its classification results [1, 13, 32, 47, 49]. Zeiler and Fergus [48] created a visualization that explains how intermediate network layers operate and what kind of features activates them. They used deconvnets to reverse the process of assigning features to pixels and thus translate feature representations into neuron activations for previous layers. Another technique for mapping classifications back to input features is Layerwise Relevance Propagation developed by Bach et. al. [4]. They preserve a relevance value for each layer and then backpropagate through the network to map classification results to input features. It is thus possible to see which input features contribute most to the classification result. These activation maps have been embedded into a visualization framework by Strezoski and Worring [41] in which users can upload a model and then visualize activations for selected layers. Guided Backpropagation was invented by Springsenberg et. al. [39] to gain insight on which parts of an image were important for the classifier. However, visualizing activations directly is rather technical and does often not provide additional information for machine learning layer models which makes it often unimportant to understand these visualizations. Instead, when applying these techniques directly to the image to be classified, intuitive heatmaps can be derived.

Classification Visualization. Other techniques visualize classification results in a more abstract way [28, 42]. This makes it easier to interpret such visualizations and thus get new insights into classifiers. One promising approach, which also obtains its visualizations from classi-
fication results is, to visualize which areas of an image contributed to the classification result and was developed by Ribeiro et al. [29] for explaining predictions. The tools they developed are helpful when comparing different classifiers, since one can see whether a model was able to detect meaningful features. It is, however, highly possible with this technique, to get an overview of entire training datasets. An approach to visualize whole datasets in combination with classification results was presented by Pavia et al. [24]. They use point-based visualizations to give insight into the structure of datasets and presented a tool to interactively modify the classification model to better match the structure of the training data. By providing this tool, one can improve model architectures based on classification results, their tools lack the capability to also change the dataset itself. Chae et al. [10] developed a tool for analyzing classification results during an iterative model development pipeline. It allows to view misclassifications and thus get insights into what the network is not good at recognizing. One can also see how classifications change over time and thus get an idea of how the learning progresses. This visualization is well suited to understand classification results. It is, however, not designed to review training data and does not incorporate a feedback loop to change data labels for improving training datasets. With the training data visualization tool facets [26], Pushkarna et al. discovered a frog that was incorrectly labeled as a cat in the well known Cifar10 dataset [18]. This was found through a confusion matrix containing classification results. They zoomed into this matrix and then discovered an image that was incorrectly labeled to be a cat when it clearly showed a frog. However, these findings are rather anecdotal and one cannot rely on them directly. Also, to our knowledge, there is no possibility to directly resolve discovered errors in any of the current visualizations. Since there are many approaches to visualize aspects of neural network classifiers, Yeager et al. [46] compared different visualizations for deep learning. They highlight different aspects that can be visualized and summarized, and classify which visualization techniques are appropriate for certain use cases. Confusion Matrices give a good overview for large datasets and are thus used in many classification visualizations [7,18]. However, confusion matrices always require the understanding and combination of both, the label and the classification axis. A user always has to match a matrix cell to a label and a classification result. This can be misleading for laymen and proved to be too complex for depicting the source and destination for misclassifications when presented to domain experts [28]. An alternative to confusion matrices for getting insight into classification results for individual classes was developed by Alsallakh et al. [3]. They invented the confusion wheel as a detailed and intuitive approach to analyze classification results. Their approach focuses on visualizing classification results for each class and then showing source and destination of misclassifications. Since we were mainly interested in misclassifications, their probability-distribution, and their source and destination, we chose not to incorporate the confusion matrices for visualizing the information space taken up by class overlap. Also, with its circular shape, it provides no clear entry point for laymen. We thus developed a linked list visualization with importance sorting focused on classification errors. Another approach for using prediction probabilities to gain insights into the classifier was presented by Katehara et al. [17]. They used prediction probabilities to visualize the performance of the classifier. Similarly, we also utilize classification results for our visualization. We, however, go one step further and use prediction probabilities to find errors in CNN training data.

Data Labeling. As the quality of labeled data plays an essential role when using CNNs, many authors have worked on visual interfaces for data labeling [11,15,34]. Our approach, however, is focused on correcting erroneous labels rather than assigning them, as labels generated through for instance crowdsourcing can result in quality problems. In this context, majority voting is often used as a solution to resolve labeling disagreements [14,16]. Other approaches to improving the quality of crowdsourcing work is to provide monetary benefits for good work, detailed framing of the work to be done or selecting the workers with predefined requirements [23,30]. All of these approaches are focusing on quality assurance while labels are acquired. This involves more cost and time effort during the data acquisition process. We, however, focus on correcting data labels after the actual labeling process through crowdservices are analyzing how the worker interacted with the system or having other workers review the work of their predecessors [14,31]. A work published by Chang et al. combines multiple of these aspects to ensure data quality by grouping multiple workers and letting them interactively reason about label decisions [11]. They use a three-step approach of first, voting for a certain label, then explaining disagreements for labeled samples with workers and then categorizing the work into a class that all workers of the group agree to. While this process does help to improve data quality, multiple workers have to be paid for the same data, the work takes more time since workers have to reiterate over certain items and sometimes even wait for other workers, and domain experts have to resolve conflicts of the categorization process. For all of these data improvement methods to be effective, crowdsourcing needs to be done by domain experts who can review the labels, refine the requirements or even conduct a separate, second task to verify the generated labels. Not only is this more expensive, it also often requires more time put into the label generation process. Sometimes the data is specific and cannot be perfectly labeled by laymen. When this is the case, experts might give the crowdbased workers basic ideas of classes and accept that some special cases cannot be handled by novices. It then is important for domain experts to be able to review the data and correct it with minimal effort themselves. In other cases, as in ad-hoc training scenarios, it is important to be able to generate reliable datasets in a short timeframe while keeping the data quality as high as possible [8]. In these scenarios, it is therefore helpful if domain experts can review and resolve label errors quickly. In scenarios where labels can be assigned automatically, it is even harder to verify the label correctness [43]. Without any visual support, the user can either review all training samples or, again, hire more workers. Our approach borrows concepts from active learning where the classifier asks the human to label those data items having most impact on classification accuracy. Our approach of analyzing classification errors is similar in spirit, as we visualize those classification results where labeler and classifier disagree. Among the active learning candidate selection strategies, our approach is most similar to the query-by-committee strategy, where the output of several classifiers is compared to inform candidate selection [35]. Beyond active learning alone, Bernard et al. have compared active learning and visual interactive labeling strategies, and found that sometimes the interactive approaches outperform active learning [5], which resulted in the combined VIAI process [6]. As we see our interactive visualizations also at the border of active learning and interactive labeling, we feel that we are inline with the reported findings.

As discussed, there are many tools to analyze and improve deep learning model architectures. However, with current technologies models cannot be optimized by laymen lacking experience in the area of machine learning. At the same time, as the usage of CNNs becomes more widespread, we see a strong need for visualizations targeted towards these users. Since training data is not as difficult to understand as model architectures, and domain experts usually know their data well, we hope that the presented visual analysis system can help to refine training data and thus helps to train more reliable and robust classifiers.

3 ERROR CHARACTERIZATION

When considering classification problems, most visualizations focus on general error metrics (e.g., [25,37]). The most basic representation of errors would be to simply calculate the classification accuracy and show it to the user. While this gives insight into whether the classifier learns at all, it does not provide feedback regarding the source of low accuracies. ROC-Curves are often used in the context of classification [9]. They are used to show the relation of correctly classified samples to false positives and thus indicate how a classifier performs. Another widely used visualization for classification results are confusion matrices, which provide an overview of how classifications are distributed by means of heatmaps [7]. While all these visual representations are useful to represent overall classification accuracy, they do not help to spot specific instances of errors in the training data which may be responsible for inaccuracies. To be able to represent the latter, it needs to be characterized which types of errors may occur on the data level. Therefore, in the context of training data labeling, we have identified three error types, which we will discuss below.

Classification Errors. Classification errors occur when images from class a are assigned to be of class b by one of the labelers. This kind of error is a conceptual one and leads to many errors in the dataset since all the labels assigned by one labeler and belonging to a class a end up with the wrong label b. A labeler thinking of gooses belonging to the class of ducks throughout the entire dataset used for bird classification would be an example for such an error source. Fortunately, class
interpretation errors are rather easy to detect, since usually all images labeled by the same person are assigned the wrong labels. As long as the majority of images is correctly labeled, our presented approach is able to guide to these errors, as will be explained in Sect. 5.2. An interesting occurrence of this type of error in the widely used MNIST dataset is the misinterpretation of the American and European way of writing the digits '7' and '1' as shown in Fig. 3.

**Instance Interpretation Errors.** When single items in the dataset get labeled incorrectly, the situation is more difficult. This can happen, e.g., when a labeler accidentally assigns a wrong label to one training image. These errors cannot be spotted by analyzing the ratio of misclassifications of one label classification pair. They are thus harder to detect and need more effort to be removed. At the same time, however, they have less influence on the classification accuracy as compared to class interpretation errors, since they do not have such a strong impact on the training results as when multiple samples are mislabeled. However, to provide means to identify and remove instance interpretation errors, we use an interactive embedding technique for the images, which will be described in Sect. 5.3. Applying this approach to the widely used Cifar10 as well as the MNIST dataset, revealed previously unknown labeling errors.

**Similarity Errors.** These errors are present when images occur more than once in the labeled dataset. This can happen, when images are taken from online sources or when an overview of the dataset is not always present in the acquisition process and images get thus added more than once. It is important to differentiate between intentionally augmented data and similar images that might overrepresent certain features during training since augmented images can lead to better training results. However, having similar images unintentionally in the labeled dataset can compromise the training results in multiple ways. When both of them are in the training dataset, higher priority is assigned to this representation of the class they belong to. This can lead to features being overrepresented in the training dataset and thus considered more important than other important features. However, this is only a problem when this overrepresentation is not expected in the productive use of the network on real-world data. When in contrast both instances are in the validation dataset, validation accuracy has higher variation depending on the correctness of the classification of these images. This might compromise the validation accuracy and thus not represent the actual performance of the classifier. Again, this is only a problem if it does not reflect real-world distributions. If similar images exist across training and validation datasets, validation is performed on an image that the classifier has been trained on, which can also compromise validation results and probably is the biggest problem regarding similarity errors. Correcting errors of this kind can be done through our similarity guidance. Similarity errors require most experience of all error types to handle, as similar images are not always a problem for the training of CNNs. They are only harmful if either, they cannot be expected to be available in the same distribution in real-world setups or if they originate from both the training and validation datasets because then, validation does not test generalizability.

In our visualizations, we make use of the suggested error characterization and treat these three error classes differently. For each of the classes, we propose special user-guidance systems that make it easier to spot and correct such errors.

### 4 User Tasks

Based on the proposed error classes we introduce the following user tasks that allow a systematic correction of errors belonging to each class. Therefore, we define a three-step approach in which, first, the user reviews the classification results for the dataset to detect suspicious entries. For this purpose, we utilize the classification results of the training dataset and present them in our visualization to quickly guide the user to such suspicious entries. After findings have been made, inspecting these is important to determine the reason for the respective characteristic. Suspicous characteristics in classification results do not always mean that there are errors in the training data. Reasons for those can also be bad network performance or, in the case of similarities, intentional multiplication of an image type. Thus, the second step after making observations in the classification results is to reason about them in order to separate training data errors from classification anomalies. This is done by inspecting individual samples. Once the user is sure she/he has detected an error in the dataset, she/he can resolve the error. We refer to detect, reason and resolve as user tasks, as these have to be performed by the user to improve the labeling data. Because not all types of errors are handled equally, these user tasks vary based on the error type at hand.

**Detect.** For spotting anomalies in classification results, we have to differentiate between all three errors types. For class interpretation errors, it is common to have many samples classified into a class that is not identical with the label of the items, i.e., many mislabeled items of class $a$ are misclassified into their true class $b$. Instance interpretation errors often are confidently misclassified since they contain the features of their true class and the classifier is sure about these classifications. In this case, very confidently but individual misclassified samples from $a$ are classified into their true class $b$. Similarity errors can be spotted by looking out for similar images in the dataset. Multiples will be classified all into the same class, as a consequence, when comparing all images classified into the same class, similar images can be spotted. We will describe in Sect. 5.2 how finding all these anomalies is supported by the proposed visual analysis system.

**Reason.** The reasons for such findings also have to be determined based on the error class. For class interpretation errors, the user has to be able to differentiate between mislabeled and bad network performance. Sometimes, a classifier is simply bad at differentiating class $a$ from class $b$ while in other cases a labeler might have confused $a$ and $b$. Resolving this is essential for confirming or rejecting candidates for class interpretation errors. Instance interpretation errors have to be differentiated from plain misclassifications that can always occur in classification scenarios. This differentiation can also be made by looking at individual samples and verifying their class membership. Similarity errors are most difficult to decide if they are problematic. The user has to reason about whether similar images were intentionally added to the dataset or compromise the training or validation process. One might intentionally add duplicates or very similar images to the dataset to make the classifier focus on properties that also occur frequently in real-world scenarios while at the same time representing certain image-types. Moreover, mislabeled images can harm the classification accuracy in productive use. Finally, similarity errors need to be distinguished from data augmentations.

**Resolve.** The process of resolving errors that have been found can also be different based on the three error classes. For class interpretation errors, users have to be able to change the label of multiple images at once to quickly relabel multiple instances. Instance interpretation errors can be resolved by relabeling individual samples one after another. Similarities that were found and classified as problematic must be removable from the dataset entirely to keep only one of the multiples. We also enable all of these actions through our visual analysis system. The entire process a user has to go through with respect to the different error types is illustrated in Table 1.

### 5 Iterative Data Refinement

In this section, we will introduce our visual analysis system, which helps to resolve the three error types introduced in Sect. 3 by means of the user tasks discussed in Sect. 4. It is important to note that the labeled dataset can be refined iteratively and resulting classifications of the network are incorporated in the visual representations as shown in Fig. 1. To detect and resolve errors, we first show an overview of the potential errors, before offering an in-detail inspection of individual labeled images. During the in-detail inspection, error types can be reasoned and eventually resolved if considered relevant. Thus, we follow the Shneiderman Mantra [36], such that the user first obtains an overview, before being able to dive into details. Inline with this mantra,
we have also realized filtering methods for the inspection.

To address machine learning laymen, we decided to simplify the used visualizations where possible. Thus, instead of using the terms label and classification in the visualizations, we simply display if an image was assigned to class \( i \) by the human or by the computer. We further try to avoid other technical details such as the sorting algorithm which was used for image embeddings. Thus, the visualizations and tools should be guiding even inexperienced users as they do barely contain machine learning terminology.

The following describes our contributions integrated into the proposed system, whereby we present metrics to detect potential errors, visualizations to guide the user to these errors, and finally interactive techniques for resolving relevant errors. We will begin by explaining the metric used for determining the confidence for misclassifications, and thus the detection of potential labeling errors. To guide the user towards these potential errors, we will further propose an overview visualization (see Subsection 5.2). From within this overview, users can inspect certain label classification pairs and inspect them within an in-detail visualization (see Subsection 5.3), where they can also resolve relevant errors (see Subsection 5.4).

### 5.1 Detecting Potential Labeling Errors

To improve the labeled data, one could inspect the entire dataset and its labels in detail before the first training run even happened. This would, however, be highly inefficient. To optimize this process, we want the user to focus only on a small subset of potential errors. Therefore, we use the CNN itself to help the user in finding errors in the labeled dataset. After the training process, we use the trained CNN to classify each training and validation image once, in order to uncover disagreements between labels and the classes determined by the CNN. It is important to include both, the validation and the training dataset since both could contain errors. The datasets are, however, not mixed in memory and do not interact in any other way than for the purpose of generating the desired visualizations. This ensures that during training the essential separation of training and validation data is maintained.

It is also important to note that this classification step is not used as a measure to validate the CNNs training outcome in any way, but simply to propose error candidates in the labeled dataset. The results of this classification are then used throughout the visualization to guide the user to potential errors of the types introduced in Sect. 3. We assume that, although the labeled data may contain errors, the CNN is still able to differentiate between different classes, such that in general incorrectly labeled images get classified into their original class. Since this makes the classification result and the original label differ, these images can be detected by looking at misclassifications in the dataset. This approach of utilizing classification results for correcting the data does, however, only work if the classifier can differentiate between the classes, i.e., the majority of the data is labeled correctly. Given the success rate of CNNs nowadays and the availability of datasets, we found this assumption safe to be made.

Besides the occurrence of misclassifications, we further exploit the fact that probability values can be retrieved from the CNN. These probability values indicate how certain the CNN is, that an image belongs to a particular class. As Chae et. al. [10] mention, it is also important, how the probability values are distributed over all classes of a labeled image and not just the class that was ranked first. We therefore consider all probability values for each image in the dataset and use them to parametrize the proposed visualizations. Those images that are more confidently misclassified are more likely to be labeling errors and less likely to be classification errors. However, this does not only depend on the probability of the classification result but also the probability that was attributed to the class the image was actually labeled to be [17]. As Atsalakis et. al [7] state:

\[
\text{score}_i = \frac{\text{prob}^\text{classification}_i + (1 - \text{prob}^\text{label}_i)}{2}
\]

Fig. 4. The list view of classifications shows problematic label/class combinations at a glance. The number of misclassifications for each cell is encoded in the blue background. The red horizontal bars in each cell show, how confidently the images have been misclassified as computed through Equation 1. Visual separation of rows makes clear, that this list should be read from left to right. On the left, one can see cells for correctly classified samples.

### 5.2 Overview Visualization

After the labeled data has been classified, the results are abstracted and shown in an overview visualization. Within this visualization, we show the classifications for all images of the entire training and validation data. The goal of this overview visualization is to guide the user to problematic label classification pairs to facilitate further inspection. Consequently, we represent label classification pairs as the main entities within this overview visualization, similarly as it is done by confusion matrices [7, 26]. While confusion matrices have shown to be effective especially for multiple inference [46], which is what we do in our visualization as well, we noticed that determining the combination of label and classification for each cell can be quite confusing for non-experts. To do so, confusion matrices have to always be interpreted with their axis in mind, which results in cognitive overload induced by required visual scanning. Furthermore, confusion matrices have to obey a fixed order of the label classification pairs, such that identical matches are displayed on the diagonal. Since the main purpose of our overview

| Class Interpretation Error | Instance Interpretation Error | Similarity Error |
|---------------------------|-------------------------------|------------------|
| Detect                    | Many samples misclassified from a to b | Samples confidently misclassified | Similar/ identical samples |
| Reason                    | Error or bad Network performance? | Error or bad Network performance? | Error or intentional? |
| Resolve                   | Reassign all labels | Reassign individual label | Remove item |

### Table 1. User tasks involved when improving training data. The user has to first, detect potential errors, then try to reason them, before he/she can resolve them. The table shows how these tasks are completed for the three identified error types.
visualization is to guide the user to problematic label classification pairs, a visualization with a clear reading order is preferable. Only then, we are able to communicate an order of label classification pairs, which directly follows the severity of these pairs such that more severe ones stick out in the visualization. Thus, to provide this overview, we utilize a sorted list layout which can be interpreted in priority order, i.e., from more to less severe cases. Figure 4 shows an example of this overview visualization. As it can be seen, the proposed list view can be read from left to right for each label, whereby the labels are sorted vertically, and displayed in the left column. To further support the desired reading order, we added horizontal lines separating the label classification pairs associated with each individual class. Furthermore, a less saturated vertical line separates those cells representing matching, i.e., correctly classified, label classification pairs, which are used to represent the classes in the left column, from those cells that indicate incorrect ones on the right. To make clear, which label classification pair is represented by each cell, we show a representative image. To ensure that this image is most representative, we selected the image that maximally activated the neuron corresponding to the desired label in the softmax layer. Thus, the selected image can be considered as a typical representative for that label. With our list view, the visual guidance scheme, and the representative images within the cells, it is easy for users to interpret the combinations of label and classification, as each row corresponds to one label, and the classifications are represented with meaningful images. To make our overview mask suitable for detecting errors in the labeled dataset, we visually encode the classification results by the derived mismatch-scores within the cells as user guidance (see Fig. 4).

**Detecting Class Interpretation Error Candidates.** To make it easy to identify cells of great interest, we sort the list based on the amount of misclassified images included in the list cells. We first sort the list row by row, placing the class that contains most misclassifications at the top of the list. Then, we sort the cells within each row, placing the cell representing the class that most samples got misclassified into at the left of each row. This process of looking at individual rows, from top to bottom and from left to right in each row simulates the natural reading direction used in the western world. In contrast to dense confusion matrices, we further only show cells that contain misclassifications, all other cells are omitted since they are of no interest to the user. Thus, our visual encoding emphasizes where to look and guides the user's attention to potentially severe cells. Another important aspect for indicating the importance of individual cells is, that cells containing many misclassified images are highlighted in blue. The color of such blue cells is defined in hsv color-space. While the hue is equal for all elements of the list, the saturation is calculated using a logarithmic scale $S_i$. This logarithmic scale is defined for the domain of $\max_{l=1}^{\text{numClasses}} (\text{score}_i^\text{wrong} \times 0.1)$. Each cell $i$ is represented with:

$$\text{score}_i^\text{wrong} = \frac{\sum_{j=1}^{\text{numImages}} \text{score}_j}{\text{numImages}}$$

(2)

and $\text{score}_j$ being the mismatch-score of the $j$-th image in cell $i$, as defined in Equation 1. One can then calculate the saturation value as percentage: $s_m = I_i(\text{score}_m^\text{wrong})$

(3)

where $m$ is the index of the matrix cell the color is calculated for. For this calculation, also only those cells that represent misclassifications are taken into account. The decision to not include correct classifications is based on the assumption, that users should look into the misclassifications to effectively spot label errors. Taking a logarithmic scale with the range defined as above, assures that cells with many classification errors are highlighted while minor misclassifications do not get visually represented that prominently. This way, the cells containing most misclassifications are not only shown at the left of each row, but those containing most misclassifications overall are also highlighted in blue. We use blue as a color, since red is already used to indicate potential errors, green was not chosen considering the problem of red-green blindness and also because green might indicate somewhat good. This naturally leaves the third basic color blue. Through this visual guidance scheme, we can guide the user towards candidates for class interpretation errors, which can then in the second step be further examined and reasoned about. Therefore, we propose a more detailed view which will be introduced in the next subsection.

**Detecting Instance Interpretation Error Candidates.** Apart from a cell’s background color, we also visualize the distribution of the mismatch-score through histograms represented by horizontal bars within each cell, whereby bars closer to the top of a cell indicate higher mismatch-scores for images classified into this cell. Bars lower in the cells signal a lower mismatch-score and thus less certainty of the CNN. This way, the user can get an overview of how confident the classifier is overall as well as how confidently it misclassified certain label classification pairs. The vertical bar position is always scaled linearly to the height of the cell in the domain of:

$$h = \frac{1}{\text{numClasses}}$$

(4)

The horizontal bars depend on the mismatch-scores as defined in Equation 1. This domain is therefore sufficient for their vertical position, since this score never exceeds $\frac{\text{numClass}}{\text{numImages}}$. To obtain this histogram, each classified image is sorted into buckets based on its mismatch-score. For these buckets, the domain of Equation 4 is divided into steps of 0.1, i.e., one bucket spans a range of 0.1 in the domain of Equation 4, and each bar represents one of these buckets. The lower bound of the domain in Equation 4 did not get scaled to the lowest mismatch-score in the dataset but was set to always be $\frac{\text{numClass}}{\text{numImages}}$. Always taking the lowest mismatch-score would have saved space, however, it would also remove insights into how sure the CNN is overall. This can be found out just by gazing at how far from the cells’ bottoms’ the bars are on average. As overall classification certainty is an important measure, we feel confident that it is worth to include the empty space in our visualization for this purpose.

To guide the user directly to misclassifications and utilize the help that CNN classification results can provide in spotting errors in the dataset, we only include these bars in cells containing misclassifications and not in cells representing correctly classified samples. Thus the first column of the list does not contain any bars. To indicate potential errors in the dataset, the bars representing these misclassifications are colored coded, whereby we use the signal color red as the general color to communicate potential problems in the dataset. To tackle the task of finding potential instance interpretation errors, the user can look at bars at the top of each cell, since these represent images that have been confidently misclassified.

**Detecting Similarity Error Candidates.** To also guide the user to similar images, we calculated the pairwise structural similarity index measure (SSIM) [44] for each image pair in each of the cells. Since it is save to assume that images causing similarity errors will be classified into the same cell, we do not have to calculate pairwise similarities for all image pairs in the dataset but can focus on images located in the same cell. In the list view, we guide the user to similar items by overlaying a duplicate symbol as shown in the ninth row and second column of Fig. 4. We add this symbol for all cells that contain image-pairs with an SSIM value of at least 0.95. Again, reasons for these images being handled as similarity error candidates can be examined further in the more detailed view which will be described in the next subsection.

The described overview visualization supports the detection step in the user tasks for all three error classes and provides visual guides for all of them. Class interpretation error candidates can be found by looking at highlighted cells, instance interpretation error candidates are indicated through bars being at the top of individual cells and similarity error candidates might be in cells marked with the duplicate symbol.

5.3 In-Detail Visualization

After selecting a specific cell $(i,j)$ in the overview visualization, with $i$ being the label and $j$ being the classification result, the system changes to an in-detail visualization showing the images associated with this cell. This in-detail visualization (see Figure 5) supports the user in reasoning about the detected error candidates. In order to investigate if images were labeled incorrectly or if they were simply misclassified, users can look at individual images. To follow the flow of the task at hand, this inspection view is located on the left side of the in-detail visualization, since reasoning about error candidates happens before acting upon them. To make the user focus on the images, the canvas that contains the image embedding is always centered in this view horizontally, while being vertically at the top. Similar images are then displayed at the bottom of the view to be reviewed in a second step. To embed all displayed
many images into that class anyway. Some useful insights here might be, when the misclassified images are similar and thus cluster in the embedding. The next step would then be to include more images of that type into the labeled dataset, for the CNN to learn the features it was previously missing out to correctly classify those images. An example for this case would be, when all walking cats are misclassified, the classifier might only know representations for sitting cats. Wrt. instance interpretation errors, images might stand out as outliers in the t-SNE embedding immediately or after correcting or confirming some images as explained in Subsection 5.4. Similarity errors can be spotted in this visualization as well, since they should be embedded closely and thus be comparable right away. However, to support the user even more in comparing similar images, we also display the most similar ones at the bottom of the visualization. They are always displayed as pairs to make them instantly comparable. This can be seen in Fig. 5. The similarity measure we take for this visualization is SSIM as described in the previous Subsection. Again, we would like to point out, that when trying to resolve similarity errors, it is important to differentiate between data augmentation and randomly similar or equal images.

To give the user tools to modify and filter the visualization of images, we included a control panel below the embedding view. t-SNE has downsides when displaying large numbers of images because of occlusion as well as when showing only few images, since then, they all get spread out into the corners of the canvas. We therefore only calculate this representation for at least 6 images in a cell. For fewer images, it is possible to overview them without any spatial embedding and they are shown side-by-side in the center of the canvas. Also, for large numbers of images, to overcome the problem of occlusion, the user can either switch to a list view with the images being sorted by their mismatch-score as defined in Equation 1. The user can also remove images from the visualization step-by-step, which will be explained in the next Subsection. Another option in this control panel is to filter the images based on their mismatch-score. We use a two-handle slider to enable the definition of a score-range for the images to be displayed. This way, the user can focus on images that were classified with a predefined certainty by the CNN.

We further encode the images from the validation dataset with a blue border. Especially for similar images, it can be interesting which part of the labeled dataset they belong to. The visualization allows a selection of individual images as well as selecting multiple images. Additionally, the control panel also displays how many images are in the current selection.

5.4 Resolving Errors

After images have been selected, the user can correct or confirm their labels in a detail view which can be seen on the right of Fig. 5. This view serves as a tool for the last user task we defined of acting upon findings that have already been reasoned about. Here, the probability-distribution of selected images is presented along with an image of the current selection. In this area, labels can be confirmed or changed by selecting to approve either the decision of the human or that of the computer. Also, when none of them were right, a completely different label can be assigned. Label confirmation is important to declutter the view and give the user a sense of progress in correcting the dataset. When labels for images are confirmed or changed, they do not appear in the view and are not included in any calculations for other visual representations of the dataset anymore. Since the discussed options are the most common actions for the user, they are presented right below the example image. When the user wants to look at the prediction results of selected images, the probability-distribution below these action buttons can be consulted. Here, users can see what probability has been assigned to which class for the selected images. Another important feature of this tool is the possibility to remove images entirely from the dataset. This way, when images are found that are not clearly one class (e.g., they show two objects) or when duplicates are found, they can be removed. Since removal should be a very rare action, this control is located at the bottom of this detail view. To resolve all three error classes (as introduced in Sect. 3), the user can either learn the multiple images simultaneously for class interpretation errors, relabel a single image for instance interpretation errors or remove images from the dataset in case of similarity errors.

To make reassignment uniformly useable, images are simply stored in folders, separating training and validation data. After reassigning or confirming a label, the images that have been selected are moved to the

Fig. 5. After gaining an overview of the classification results, the user can inspect the content of individual cells to analyze classification results in detail. Images are embedded by applying t-SNE to saliency maps. Filtering can be done by selecting mismatch-score ranges. Once one or more images have been selected, the according probability distribution is visualized. Selecting a bar in this distribution changes or confirms the label of the selected images.

Fig. 6. Original images (top row) and the corresponding color-enriched saliency maps (bottom row). In our approach, we use the saliency maps for the t-SNE embedding, in order to distinguish based on which features images have been classified.
were able to spot an image of a three in the MNIST dataset which was wrongly labeled as a five. A larger version of the image can be seen on the right.

The Cifar10 dataset consists of tiny, 32 by 32 pixel colored images from ten different classes, and is also often used as image classification benchmark. We used this dataset and trained it with its original labels. The model used for training was built by two convolutional layers followed by a pooling and a dropout layer. This setup was then repeated once more and followed by two dense layers each also preceding a dropout layer. Then, the final softmax layer to obtain the classification was added. Again, all layers except the last used the ReLU activation function. With this very simplistic network, we reached an accuracy of 77.13 percent which might well represent the performance of a network designed by laymen.

We did a systematic data clean-up in which we checked misclassifications step-by-step as described in Sect. 5 and by inspecting several cells that were highlighted. Even with the classification accuracy we reached, when looking over all cells on the right of the list, we only had to look at 12.87 percent of the data. This equals only about 7700 of 60,000 images. When performing an in-detail inspection of the cell that represented the label cat and the classification frog, we found an incorrectly labeled image by iteratively removing outliers from the t-SNE embedding. As one can see in Fig. 8, it did not take many steps with our systems to find an instance interpretation error in a well-known dataset.

Another interesting insight that we got when investigating the Cifar10 dataset was, that there are some images that are similar. Through the SSIM calculation we use to visualize the similarity of images, we were able to find these in the dataset. Examples for such images can be seen in Fig. 9.

6.3 Skulls

We further examined a dataset containing x-ray images of skulls of different mammals. The greyscale images were of size 256 by 256. We adopted the network architecture from the Cifar10 dataset by just adjusting input and output sizes, and we classified the images into the animal types as classes. We first used a small subset of three classes and then included 22 animal classes into the visualization. The results of these training runs can be seen in Fig. 10. It nicely illustrates that our approach works with larger datasets as well.

7 User Study

To test the proposed visual analysis system, we conducted a study in which 10 participants had to find and resolve errors in a labeled dataset. Participants were recruited in a University setting, whereby out of the 10 participants, only two had experience with neural networks and none of them had seen our visualizations before. Thus, the participants nicely reflected typical laymen users.

We chose to use the MNIST dataset in our study since no prior knowledge is required to review the labels of the images. To be able to verify which items have been changed by a participant, we corrupted the dataset by introducing five errors of each type. For class interpretation errors, we changed 1400 images from nine to six, 700 images from one to four, 700 images from three to one, 350 images from eight to two and 175 images from seven to three. To reflect the original distribution...
of images, we always took images in a relation of 6:1 for training and validation respectively. For instance interpretation errors, we changed the labels of five images from different classes. Similarity errors were introduced by duplicating five images. For both of these, one of the five images belonged to the validation dataset. In total, we introduced 3330 mislabeled images and five duplicates. We then trained on this dataset and visualized the results with our system. The classification accuracy for this manipulated dataset was at 94.37 percent, hence, our system only presented the 5.63 percent that were misclassified to the participants. This equals to about 4,000 out of the 70,000 images. We provided a short introduction of about 10 minutes which showed our visualizations and explained the task, which was to resolve as many errors as possible in 15 minutes. We then let them use the visualizations proposed in this paper to resolve all errors they spotted.

With our duplicate guidance, all participants were able to resolve all duplicates. On average, every participant changed the labels of 2902 images, of which only 27.5 were incorrectly changed. They thus managed to bring the number of incorrect labels down by 85.65 percent on average. This is a reduction to 477 errors from 3330 after only one iteration of De-Confusion. We then used the corrected datasets to train the classifier once for each participant. On average, the validation accuracy rose to 99.05 percent, which means that, when before 4000 of the images were misclassified, only 665 misclassifications were left after the participants corrected the dataset in one iteration. One interesting insight was also gained when looking at the images that we initially considered as incorrectly changed. When investigating them, we found that many of them seemed to be mislabeled in the original dataset. The participants thus found new errors in the well-established MNIST dataset by using our system. Examples of these errors are included in the supplementary material.

We also asked the participants to rate the helpfulness of our visualizations when compared with resolving the errors in any other way. They had to rate the helpfulness of the visualizations from one, not helpful at all, to five, helped a lot, of all of them rated the visualizations between four and five, with an average of 4.4. When asked what they found most helpful, most of them said the overview list was very helpful for spotting errors in the dataset. Some also mentioned that the enlarged view of the images was very helpful to compare them.

When asked what was bad and could be improved, many said that the latency was a problem. This was due to the study being conducted over the internet. Since images had to be transferred, sometimes users had to wait for all of them to appear. This should, however, be a problem specific to the study setup and not to our system per se. Also, some participants mentioned that for large numbers of images, the embedding could get cluttered.

Since there is no other tool dedicated to correcting the dataset, we could not compare our methods to existing ones. When regarding file explorers for performing this task, users would have to look at every individual item once more without any guidance. Thus, we chose not to compare against this method since spotting errors in the explorer at all was very difficult, and correcting a dataset in 15 minutes when looking at images displayed in a file-browser was simply impossible for users who tried it in a pre-study. Also without such a comparison, we feel that it is safe to conclude that the results of the conducted experiment show the benefits of the proposed system clearly. All participants were able to improve the dataset by a large margin and thus greatly improve classification accuracy.

8 LIMITATIONS

While we could demonstrate the utility of our approach by detecting errors in well known image classification benchmark datasets, it has also some limitations, which we address in this section. One such limitation is that for a large number of classes, the overview visualization might get too cluttered to be interpretable. Furthermore, in the in-detail visualization, single images cannot always be spotted since they are sometimes occluded by other images. Additionally, our techniques are based on the assumption that the classifier is somehow able to distinguish classes. Thus a classifier that is able to learn matching features is required. Also, a sufficient portion of the training data has to be labeled correctly for the CNN to be able to learn feature representations that match the dataset. Thus, only images that have been recognized by the classifier as being wrong can be effectively spotted.

9 CONCLUSIONS AND FUTURE WORK

Within this paper, we have proposed a visual analysis system, which has been tailored such that machine learning laymen can improve their training data for image classification tasks. To our knowledge, this has been the first time, that this problem has been targeted explicitly using visual representations of training datasets. The approach presented in this paper can be used to correct any labeled image dataset trained on any CNN. To do so, we have characterized relevant error types and proposed user tasks leading to a resolution of these errors. By means of a tailored overview visualization, it becomes easy to spot problematic classes, and then perform an in-detail inspection by means of an embedding of the training data that utilizes classification results. Also, we highlight similar images throughout our visualizations. With these techniques, we enable the detection of all three error classes which we differentiate. Within the in-detail visualization, users can then directly change or confirm labels, or remove images from the dataset. Thus, we support a step-by-step approach mapped to the user tasks identified in Sect. 4. The efficiency of our approach highly depends on the classifier performance. For well trained classifiers, users have to check far fewer images for correctness since they only have to check for the classifier to agree.

The proposed system is the first of its kind, that is explicitly dedicated to improving training datasets for CNNs. When tested in a study, participants were able to improve the classification accuracy by resolving label errors in only 15 minutes. They were able to resolve most errors and even found flaws in an original benchmark dataset.

For future work, we would like to experiment with incorporating user feedback from the visualization into the training process. Confirmed items could, for example, be weighted higher than those that have not yet been confirmed by the user. Another interesting area of research would be to create tools capable of finding incorrect images that the classifier does not recognize. One would have to come up with different metrics for error candidates in this case.
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