Other related work concerns the use of tags on pictures in social media. Though the relationship is not entirely intuitive between the usual tags and tags that we use for this project, one of our approaches relies on self-tagged pictures from a social media platform, Flickr, that give hints to the time (for example, a picture might have the tag "afternoon" or "night" included). In the publication User Conditional Hashtag Prediction for Images (a collaborative effort between New York University and Facebook AI Research), users were modeled by their metadata to perform "hashtag" prediction by photo [2]. The team found that the addition of user information gave a significant performance boost. They found, however, that when working on real world datasets rather than curated ones, the highly skewed natures of "hashtags" needs to be addressed by downsampling the more frequent hashtags to produce more varied predictions. While modeling Flickr users is beyond the scope of this project, this conclusion led us to the hypothesis that introducing related but rarer image tags (along with the common "afternoon", or "morning" ones) would allow us to gather a more diverse dataset as well.

3. Dataset

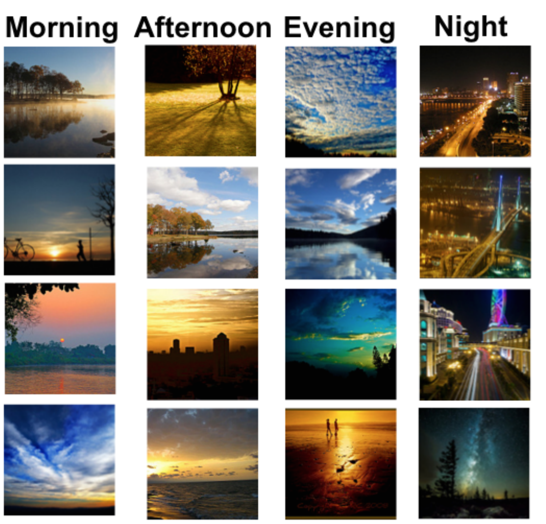

Figure 1: Sample data from the dataset

The dataset of images was collected from Flickr using the Flickr API. We collected a dataset of 3766 images which are all the images on Flickr that contained EXIF data and were relevant to the scope of the project. All images had 3 channels, Red, Green and Blue and were 150x150 pixels large. Figure 1 shows sample data from our collected dataset. We originally intended to gather all of the most recent images related to the corresponding tags to generalize our algorithm but we realized that many of the images in the dataset (for example, of close-up shots of food or faces) would not be suitable for our purposes. There were many grayscale images that would most likely only introduce noise to our model, as such, we had to filter them out. Additionally, many pictures taken indoors did not clearly correspond to the time tags presented. In keeping with our hypothesis that introducing additional tags leads to a more diverse dataset, we experimented with tags such as "outdoor" and "sky", though ultimately we reverted back to the original ones (namely "morning", "afternoon", "evening", and "night") since we decided to be consistent with the tags used for collecting the datasets. The images were sorted using the Flickr API sorting tag "most interesting" descending, as we observed that these were usually more vivid and accurate portrayals of the time tags they depicted.

Table 1: Data distribution based on image tag

Image Tag	Count
Morning	989
Afternoon	759
Evening	990
Night	1,028
Total	**3,766**

Table 2: Data distribution based on time window

Time Window	Count
[12am, 6am)	367
[6am, 12pm)	930
[12pm, 6pm)	933
[6pm, 12am)	1,536
Total	**3,766**

We approach two image classification problems: time window and tag. In the time window problem, the goal is to classify the time window in which the photo was taken, where we have the four time windows [12am, 6am), [6am, 12pm), [12pm, 6pm), and [6pm, 12am). In the tag problem, the goal is to classify the tag which was used to search and collect the image, where we have the four tags "morning", "afternoon", "evening", and "night". Table 1 illustrates the data distribution by image tag and Table 2 illustrates the data distribution by time window.

3.1. Pre-processing

We preprocessed the images to increase the accuracy of our models. The two techniques that we used were data augmentation and application of adaptive histogram equalization on the dataset to make a new dataset.