Power System Technology
ISSN:1000-3673

Received: 16-11-2023 Revised: 05-12-2023 Accepted: 22-12-2023

Optimizing Image Classification Through Preprocessing and Feature Engineering Techniques

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ABSTRACT

A collection of labelled photos obtained from several sources (such as repositories and sensors) is used in this investigation. In order to assess the efficacy of the model, the dataset is partitioned into three parts: training, validation, and test. The data is improved and the model's resilience is increased by applying image preprocessing techniques including scaling, normalization, and augmentation. Three machine learning techniques are investigated: Random Forest Classifier, k-Nearest Neighbors (kNN), and Convolutional Neural Networks: CNN. The CNN model gets an impressive test accuracy of 84.39% and a training accuracy of 91.12%. After evaluating each model's performance using accuracy, precision, recall, and confusion matrices, the kNN classifier achieves 63.08% accuracy while the Random Forest Classifier achieves 69.83% accuracy. The results of this study provide light on how various models do when faced with picture categorization problems.

Keywords: Image Classification, Feature Engineering, Accuracy, Machine learning

I. INTRODUCTION

Classifying images has become an essential part of computer vision and AI in this age of rapid digital transformation because to the explosion in the amount of available picture data. Many different kinds of applications rely on image classification, which involves labeling or classifying images according to their visual content. This is especially true in fields like medical diagnostics, autonomous driving, face recognition, e-commerce, and satellite image analysis. Researchers and practitioners alike face an increasingly difficult but crucial task: efficient and accurate categorization in the face of ever-increasing volumes, complexity, and variety of picture data. The use of strong preprocessing and feature engineering methods has become an essential strategy for overcoming these obstacles. These methods boost the efficiency of classification models by improving the quality of the images used as inputs and by extracting useful information from them.

The picture classification pipeline begins with preprocessing, which is both the first and most

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important step. This process is a set of steps used to prepare images for analysis by cleaning and standardizing the data, reducing noise, and improving the quality of the images. How well feature extraction and model training work is heavily dependent on the reliability and accuracy of the images used as inputs. Data augmentation, histogram equalization, normalization, scaling, noise reduction, and grayscale conversion are common preprocessing techniques. These techniques make sure the photos are of the same size and shape, draw attention to the important parts, and hide the rest. To train machine learning models more quickly and reliably, normalization is useful for things like bringing pixel intensity data into a standard range. Histogram equalization and similar methods improve contrast, which in turn helps classifiers identify important features.

Preprocessing also includes noise reduction, which seeks to remove or reduce distortions brought about by things like bad lighting, sensor mistakes, or environmental variables. Common techniques used for this purpose include bilateral filtering, Gaussian filtering, and median filtering. To further enhance model generalizability, data augmentation techniques like as flipping, translating, zooming, and rotating are used to artificially enlarge the training dataset. Augmentation strengthens the classifier's resistance to real-world fluctuations and helps decrease overfitting by subjecting the model to several picture alterations. Therefore, preprocessing is an essential part of making sure the classification process uses high-quality information.

Feature engineering is the next crucial step after picture preprocessing. The process of feature engineering entails efficiently representing pictures' content by extracting and selecting pertinent qualities or characteristics from images. The success of the classification task is heavily dependent on the quality of these characteristics. Images' texture, color, shape, and edge information were traditionally extracted using features that were hand-crafted. Classical picture classification frameworks have made extensive use of techniques like Histogram of Oriented Gradients (HOG), Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), and Local Binary Patterns (LBP). The goal of these techniques is to improve classification accuracy by extracting features that are invariant and discriminative and can resist changes in size, rotation, and illumination.

When it comes to object identification and detection, for instance, HOG excels in capturing gradient and edge structure. SIFT and SURF are well-suited for image matching and retrieval applications because to their ability to detect stable key points and descriptors. When it comes to texture classification and facial recognition, LBP is the way to go since it records the connection between pixels and their neighbors. Identifying the most relevant characteristics for a specific issue using these traditional approaches requires domain expertise and substantial testing. Although they struggle with high-dimensional and complicated data, hand-crafted

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ISSN:1000-3673
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features have helped us grasp why feature representation is so important for picture categorization.

II. REVIEW OF LITERATURE

Forke, Chris-Marian & Tropmann-Frick, Marina. (2021) Nowadays, spatio-temporal data is being utilized by an increasing number of applications for various objectives. Particular care is required when dealing with this one-of-a-kind data type to ensure its efficient processing and application. Machine learning algorithms for spatio-temporal data engineering and methodologies and approaches for selecting spatio-temporal data features are summarized in this work. In addition, it draws attention to important research in certain fields. Data processing is open to a broad variety of methodologies. However, certain adjustments to data processing procedures are required for these methods to be practically and meaningfully applied to the spatio-temporal data. Features engineering is a crucial phase.

Cesar, Ivan et al., (2020) Optimisation of picture preprocessing is a difficult topic with many potential applications, the primary focus of our work being object recognition and categorization. Every deep learning researcher knows how important it is to improve the performance of picture preprocessing in terms of processing time. In this article, we will go over some typical blunders and errors that people make during training, as well as some methods for identifying and avoiding these problems. In this work, we examine the effects of various augmentation orderings on CPU utilization and assess many popular Python modules used for picture preprocessing.

Isa, Sani et al., (2019) Sentiment analysis refers to the technique of quantitatively assessing a text that conveys a mood or impact. The optimal accuracy was achieved by comparing several methods of feature extraction, machine learning, and parameter optimization. Using a combination of machine learning classification algorithms like Support Vector Machine (SVM), Naive Bayes, and Decision Tree, this paper suggests a method for extracting the comparison value of sentiment reviews using three features extraction: Word2vec, Doc2vec, and Terms Frequency-Inverse Document Frequency (TF-IDF). The feature extraction and classifier parameters are optimized using a grid search technique. Accuracy is the metric by which these classification algorithms are judged. Using grid search hyperparameter optimization on varied pre-processed data, the technique utilized in this study increased the classification accuracy for all feature extractions and classifiers.

P T, Bharathi & Subashini, Parthasarathy. (2011) The use of artificial neural networks for picture preprocessing is discussed in this article. A variety of neural networks are used, including feed-forward, Kohonen feature maps, back-propagation, multi-layer perception, and Hopfield nets. A new two-dimensional taxonomy is used to classify the different applications.

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ISSN:1000-3673

Received: 16-11-2023 *Revised: 05-12-2023* *Accepted: 22-12-2023*

Data reduction or feature extraction, segmentation, object identification, picture interpretation, optimization, and preprocessing are all types of tasks that may be specified along one dimension. Along with the pixel-level, local feature-level, structure-level, object-level, object-set-level, and scene characterisation levels of abstraction, the second dimension encapsulates the algorithm's processing of the incoming data. An technique based on neural networks has unique limitations when faced with each of the six problem categories. There is a compilation of open issues concerning the use of neural networks and pattern recognition methods in image processing. The paper's goal in conducting this study is to identify the key benefits and drawbacks of using neural networks for image processing.

III. RESEARCH METHODOLOGY

Dataset Preparation

Images and labels denoting various types or categories make up the dataset used in this investigation. Metadata, which includes information about the picture's size, resolution, and color channels, is saved with each image in a standard format like JPEG or PNG. The dataset could originate from a number of places, including open-source picture libraries, private databases, or data gathered by cameras and sensors. To avoid bias and boost the model's generalizability, it's crucial to make sure the dataset covers a broad range of situations and problems that pertain to the issue domain. Separating the dataset into training, validation, and test sets allows for the evaluation of the model's performance on unknown data, which helps to determine its actual predictive potential.

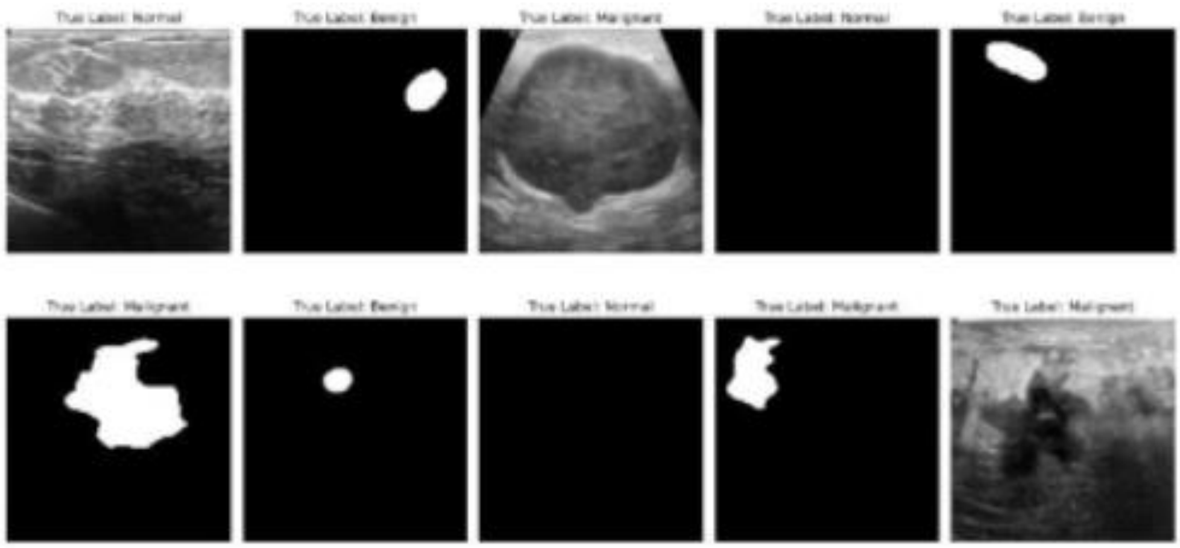

Figure 1 Color Channels of images and labels

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Data Preprocessing

The process involves many processes, including resizing, normalization, and augmentation, for picture datasets. Simplifying processing and reducing computer complexity, resizing guarantees that all photos have a constant size. To facilitate faster convergence during model training, normalization transforms pixel values to a common range, usually 0 to 1 or -1 to 1. The goal of data augmentation is to systematically enhance the size of the training dataset by generating updated copies of existing photos. Actions like rotating, flipping, cropping, and adjusting colors fall under this category. Training the model with a broader array of pictures is one way that augmentation helps it become more robust and better at generalizing.

Feature Engineering

A subfield of feature engineering known as "image preprocessing" is concerned with getting picture data ready to be fed into ML models. Improving the quality and usefulness of photos is the goal of these several phases. To decrease dimensionality and computing effort, grayscale conversion is a frequent approach. This is especially true when color information is not essential for the job at hand. Another preprocessing step, histogram equalization, spreads out the most common intensity values to increase picture contrast. If the lighting is bad, the pictures are too dark, or both, this may be a lifesaver. Image processing algorithms and other tasks may benefit from the use of filtering methods like median filters or Gaussian blur to smooth out pictures and decrease noise. For applications like object identification and picture segmentation, edge detection algorithms like Canny, Sobel, and Laplacian are used to highlight the boundaries inside images. Isolating items of interest from the backdrop using image segmentation methods (which split an image into meaningful sections) also helps the model concentrate on significant aspects of the picture by removing the background.

Model development

Three separate algorithms—Random Forest Classifier, k-Nearest Neighbors, and Convolutional Neural Networks—are investigated in this research. diverse kinds of data and activities call for diverse algorithms, each with its own set of strengths and weaknesses.

IV. RESULTS AND DISCUSSION

Training and Validation Accuracy and Loss (CNN)

We measure the CNN model's performance by looking at its loss metric, accuracy during training, and validation. During training, the accuracy reflects how well the model performs on the training dataset; for assessment of generalizability, the validation accuracy reveals how

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well it works on a different validation dataset.

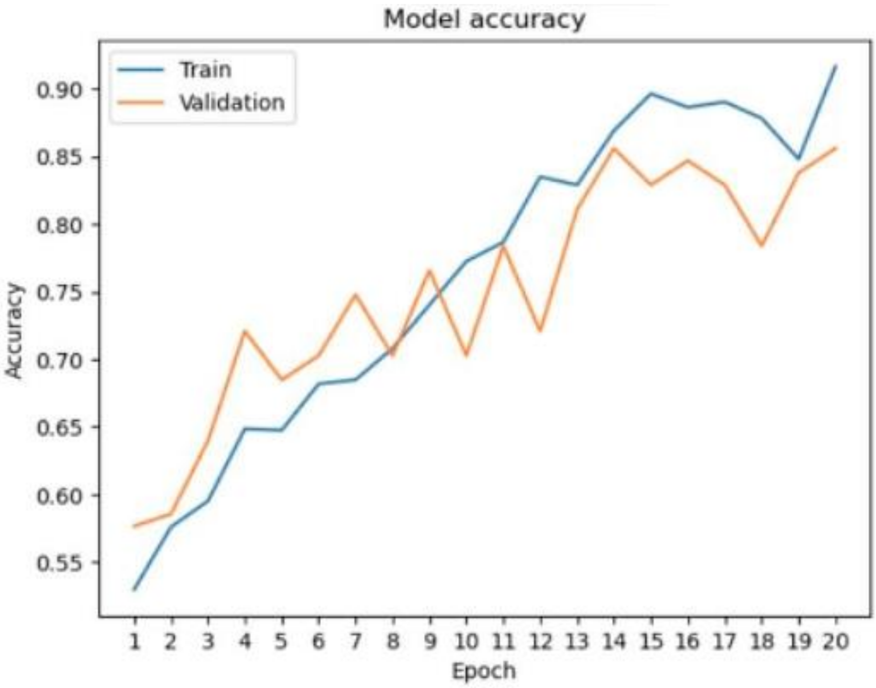

Figure 2 Model Accuracy

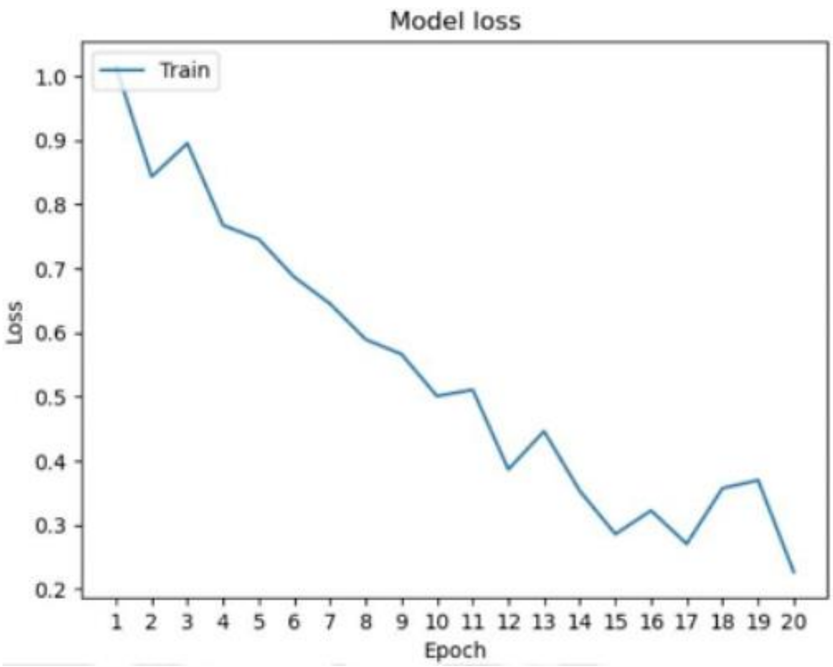

Figure 3 Model Loss

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Over 91% of the training samples had their classes accurately predicted by the CNN model, which resulted in a training accuracy of 91.12%. The training loss, which quantifies the model's inaccuracy while being trained, came at 0.257. If the number is low, it means the model trained well and reduced its error to a minimum. An accuracy of 84.39% was attained by the CNN model on the validation dataset, also known as the test set. Impressive performance on new data was shown by the equivalent test loss of 0.411, which was somewhat more than the training loss but still well within the acceptable range.

The model's learning behavior may be better understood by visualizing its accuracy and loss across epochs. The model learns from the training data and generalizes well to unseen validation data, as seen by the accuracy plot, which demonstrates an improvement in both training and validation accuracy across epochs. Likewise, a declining trend in the loss plot indicates that the model's predictive performance becomes better throughout training.

kNN Classifier Performance

Results from classifications and the accuracy of the k-Nearest Neighbors (kNN) Classifier are used to measure its performance. On the test set, the kNN Classifier attained a score of 64.08%. Support values show the number of occurrences in each class, while accuracy, recall, and F1-score are presented for each of the three classes (0, 1, and 2). To learn more about the kNN Classifier's performance in classifying data, refer to the classification report. The F1-score is a metric that takes into account both recall and accuracy; recall measures the percentage of genuine positives among all real positives, while precision reflects the proportion of all occurrences predicted as positive. All of these measures add together to show how well the classifier does when it comes to identifying distinct classes.

Random Forest Classifier Performance

Both the accuracy and the clarity of the Random Forest Classifier's confusion matrix are used to evaluate its performance. A test-set accuracy of 69.83% was attained using the Random Forest Classifier. You can see how well the classifier did across all classes in the confusion matrix, which shows the percentage of correct, negative, and incorrect predictions. The classifier's predictions are broken down in the confusion matrix, which shows where it excels and where it could mislead certain classes. If you want to know how to make your model better at detecting unusual classes or decreasing false positives, you should look at the confusion matrix.

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V. CONCLUSION

The results show that different machine learning algorithms perform well when it comes to picture categorization. When compared to the other models, the Convolutional Neural Network's (CNN) superior accuracy across training and test datasets is indicative of its strong capacity to generalize to novel data. Although they performed somewhat worse than CNN, the Random Forest Classifier and k-Nearest Neighbors (kNN) Classifier both demonstrated encouraging outcomes with accuracy ratings suggesting their potential for picture classification tasks. Analyzing each classifier's accuracy, recall, and F1-scores in depth highlights how important it is to pick a model according to the task's needs. In sum, the findings provide the groundwork for future advancements and applications in many fields by demonstrating the significance of dataset quality, preprocessing methods, and model selection in developing strong image classification systems.

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ISSN:1000-3673

Received: 16-11-2023 *Revised: 05-12-2023* *Accepted: 22-12-2023*

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