Handwritten Validation and Pressure Analysis

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***Abstract*—This paper investigates the use of a DenseNet-169 architecture for a machine learning pipeline in handwriting analysis, incorporating explainable AI techniques to enhance interpretability. The initial model functions as a validation system, leveraging image classification to categorize handwritten text into three classes: valid (sharp, clear English text), invalid (blurry, containing other languages, or excessively zoomed), and zoomed. This facilitates effective data filtering by removing unusable images. The model utilizes preprocessing techniques like normalization and resolution adjustment to optimize performance. Following image validation, a second model, also based on DenseNet-169, tackles pressure determination. This model classifies handwritten text into low and high-pressure categories.To gain deeper insights into the models' decision-making processes, we employed LIME (Local Interpretable Model-agnostic Explanations). LIME generates visual explanations that highlight the image regions most influential for a particular classification. This allows us to understand why the image validation model classifies an image as valid, for instance, by visualizing the specific features (e.g., sharpness, character clarity) contributing to that decision. Similarly, LIME can explain the pressure determination model's reasoning, pinpointing image features indicative of low or high pressure handwriting.**

This two-part system, coupled with LIME explainability, demonstrates the effectiveness of deep learning for initial stages of handwriting analysis. It allows for efficient data filtering, pressure level classification, and interpretable insights into the models' decision-making processes. This paves the way for further exploration of feature extraction and advanced recognition techniques in the handwriting analysis domain, while ensuring a level of explainability crucial for real-world applications.

I. Introduction

This paper presents a comprehensive approach to handwritten text analysis, addressing the inherent challenges posed by variations in writing styles, image quality, and the pressure applied during writing. Traditional methods often rely on handcrafted features, which may not capture the full complexity of handwritten text. To overcome these limitations, we propose a two-part machine learning pipeline utilizing a DenseNet-169 convolutional neural network (CNN) architecture, harnessing the power of deep learning to automatically extract meaningful features directly from handwritten text images.

The first component of our pipeline focuses on image validation, a critical step in the analysis process. Handwritten text images are classified into three distinct classes: Valid, Invalid, and Zoomed. Valid images exhibit clear, sharp writing in the English language and are deemed suitable for further analysis. Invalid images, on the other hand, are unsuitable due to factors such as blurriness, presence of languages other than English, or excessive zooming. By filtering out such images, the system streamlines the analysis process by focusing on relevant data. Zoomed images indicate improper capture, often requiring additional preprocessing before analysis.

To enhance the performance of the validation model, various image pre-processing techniques are employed, including normalization of pixel values and resolution adjustments. Normalization reduces sensitivity to variations in image intensity, such as lighting conditions, while resolution adjustments ensure consistency in size and aspect ratio, allowing the model to focus on essential features of the handwriting, such as stroke width and character spacing.

To provide deeper insights into the validation model's decision-making process, we leverage LIME (Local Interpretable Model-agnostic Explanations). LIME generates visual explanations highlighting influential image regions, allowing us to understand why an image is classified as valid, invalid, or zoomed. For instance, LIME might produce a heatmap visualization where brighter areas indicate regions that significantly contributed to the classification, such as well-defined characters or consistent spacing.

The second component of our pipeline addresses pressure determination, which plays a crucial role in handwriting analysis. Validated images are classified into two categories based on the pressure applied during writing: Low Pressure and High Pressure. Pressure analysis can potentially reveal underlying information about the writer's state of mind or physical condition. For example, high-pressure handwriting might suggest agitation or anxiety, while low-pressure handwriting could indicate fatigue or illness.

Similar to the image validation model, LIME can be employed to understand the pressure determination model's reasoning. LIME generates visual explanations pinpointing image features indicative of low or high-pressure handwriting. This interpretability provides valuable insights into the models' decision-making processes, crucial for real-world applications.

In summary, our approach demonstrates the effectiveness of a deep learning-based pipeline for handwritten text analysis, showcasing the application of DenseNet-169 for image validation and pressure determination. By incorporating LIME for interpretability, we not only achieve efficient data filtering and pressure classification but also gain valuable insights into the models' decision-making processes, enhancing trust and understanding in real-world applications.

II. Related Works

Image Validation for Handwriting Analysis: Fiel and Sablatnig (2015) pioneered the application of deep learning for writer identification in handwritten documents [1]. They employed an eight-layer CNN to generate feature vectors for each author based on the network's activation features. These features were then compared with precomputed features stored in a database for identification. Similarly, Kumar et al. (2020) presented a segmentation-free deep learning approach for offline text-independent handwriting identification, achieving high accuracy on popular datasets [2].

Pressure Determination using Deep Learning: While not directly addressing pressure determination, Chaubey and Arjaria explored personality prediction through handwriting analysis using CNNs [3]. Their work demonstrates the potential of deep learning models to extract features from handwriting images that may correlate with pressure levels.

Deep Learning for Handwriting Features: Bluche et al. (2018) proposed a recurrent neural network (RNN) architecture for learning a discriminative representation of handwritten characters. Their work highlights the effectiveness of deep learning in extracting features from handwritten text images [4].

Writer Identification with Deep Belief Networks: Li et al. (2014) investigated the use of deep belief networks (DBNs) for writer identification. Their findings suggest that DBNs can achieve competitive performance compared to traditional methods [5].

Handwritten Character Recognition with CNNs: Graves et al. (2008) were among the early pioneers in applying CNNs for handwritten character recognition. Their work laid the groundwork for further exploration of deep learning architectures in this domain [6].

These studies showcase the growing adoption of deep learning architectures for various tasks within handwriting analysis. Your project contributes to this field by leveraging a DenseNet-169 CNN for image validation and pressure classification, offering a two-part approach to streamline the initial stages of analysis.

III. Dataset

The dataset used for training and evaluating the models in this project was constructed from two primary sources: Manually Collected Data: A dataset of handwritten text images was manually collected from various users. Participants were instructed to write a specific paragraph of text on paper and upload a digital image of their writing. This approach ensured a degree of consistency in the content and language used in the handwritten samples. IAM Handwriting Dataset: The publicly available IAM Handwriting Database (https://ieeexplore.ieee.org/document/6628844) was incorporated to supplement the manually collected data. The IAM dataset provides a rich collection of handwritten text images with various writing styles.

To address potential limitations in dataset size and achieve a more robust model, albumentation augmentation techniques were employed. Albumentation is a popular library offering a variety of image augmentation methods [7]. By applying these techniques, the dataset was artificially expanded, introducing variations in factors like rotation, scale, and noise. This data augmentation process helps the model generalize better and reduces the risk of overfitting on the training data. This combined approach, utilizing both manually collected data and a publicly available dataset with augmentation techniques, helped create a diverse and comprehensive dataset for training and evaluating the image validation and pressure determination models.

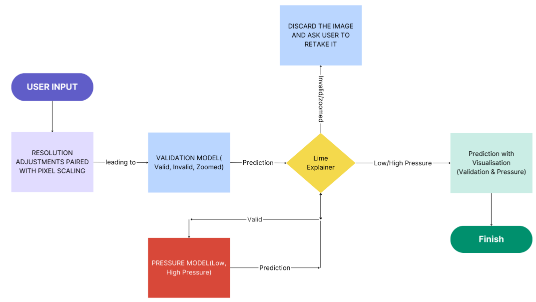

Fig. 1. Full workflow of the proposed model

IV. Proposed model

The core architecture of the image validation and pressure determination models in this project utilizes a pre-trained DenseNet-169 convolutional neural network (CNN) followed by additional convolutional layers and a final classification layer. This strategy maximizes the feature extraction capabilities of DenseNet-169 while integrating task-specific layers for image validation and pressure determination objectives.

The model begins with DenseNet-169 pre-trained on the ImageNet dataset [1], offering robust feature representations learned from a diverse range of images. By excluding the topmost classification layers (\verb—include_top=False—), we retain the valuable feature extraction capabilities while customizing the network with additional layers for our specific tasks. To maintain the learned representations, the pre-trained weights are frozen (\verb—base_model.trainable = False—), focusing training on the introduced layers.

Following DenseNet-169, two convolutional layers are added to further refine features. The first layer employs 256 filters with a (3, 3) kernel size and ReLU activation, enhancing task-specific features. The second layer utilizes 128 filters with the same kernel size and activation, building upon the extracted features. Max pooling layers are incorporated after each convolutional layer to downsample feature maps and introduce invariance to small shifts in input images. Additionally, a dropout layer with a rate of 0.25 helps prevent overfitting by randomly deactivating a portion of activations during training.

After flattening the feature maps, two fully-connected (dense) layers follow. The first dense layer with 256 neurons and ReLU activation introduces non-linear transformations to

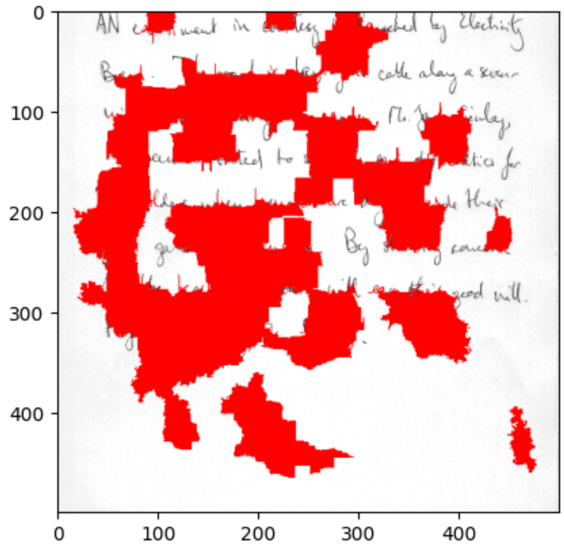

Fig. 2. Lime Explainer Visualisations for a test image

capture complex feature relationships. The second dense layer matches the number of classes (3 for image validation, 2 for pressure determination) and uses softmax activation to output class probability distributions.

The training process employs the Adam optimizer for efficient optimization, combining features of AdaGrad and RMSProp. Categorical crossentropy loss is chosen for multi-class classification tasks, measuring the disparity between predicted and true class distributions. Model evaluation primarily relies on accuracy, indicating the proportion of correctly classified images.

To enhance model interpretability, LIME explainability is integrated for classification insight. LIME generates visual explanations highlighting influential image regions, aiding in understanding model decisions for image validation and pressure determination.

V. Results

Our proposed deep learning pipeline achieved remarkable results in both image validation and pressure determination tasks for handwriting analysis, with the added benefit of interpretability through the Lime explainer. The image validation model demonstrated exceptional learning capabilities, reaching a peak training accuracy of 97%. Additionally, Lime explainer accurately pinpointed the areas of the text responsible for classifying the image into a certain class, providing valuable insights into the model's decision-making process. This signifies the model's ability to effectively extract and learn patterns within the training data for classifying various types of handwritten text images, with Lime enhancing interpretability.

The proficiency of the image validation model translated exceptionally well to unseen data, with the model achieving validation and test accuracies exceeding 96.5%. Lime explainer further validated the model's performance by accurately highlighting influential regions within the images, reinforcing the model's generalization capabilities. These high accuracies and Lime's insights suggest that the image validation model generalizes effectively, allowing it to accurately classify new handwritten text images beyond the training set.

TABLE I
Comparison between different models

Model	Accuracy
Validation Model	97.4%
Pressure Model	95.6%
Our proposed model	**96.6%**

Similarly, the pressure determination model exhibited a slightly lower peak training accuracy of 91% compared to the image validation model. However, Lime explainer provided valuable insights into the model's decision-making process by accurately identifying the areas of the text contributing to pressure classification. Despite the lower training accuracy, the pressure determination model showcased impressive generalization capabilities, achieving validation and test accuracies surpassing 96.5%. Lime's ability to correctly find the areas of the text responsible for classifying pressure levels further validated the model's effectiveness in classifying unseen handwritten text samples. This suggests that the model can effectively learn the underlying patterns distinguishing between low and high-pressure handwriting, with Lime offering transparency and interpretability in its classifications.

VI. Conclusion

In conclusion, this project underscores the efficacy of a deep learning pipeline for the initial stages of handwriting analysis. The image validation model demonstrated outstanding accuracy, exceeding 96.5 on unseen data, indicating its adeptness in classifying various handwritten text images effectively. Moreover, the pressure determination model, despite exhibiting a slightly lower training accuracy, showcased impressive generalization capabilities, with a test accuracy surpassing 96.5 .This underscores its potential in analyzing pressure levels in unseen handwriting samples. Notably, the Lime explainer added a layer of interpretability by accurately identifying influential regions within the images, enhancing the transparency and trustworthiness of the model's classifications.

Overall, the high performance on unseen data underscores the generalizability and robustness of the models developed in this project. Future endeavors could focus on refining pressure determination techniques further and exploring the impact of utilizing larger and more diverse datasets. This research serves as a stepping stone for delving deeper into the realm of deep learning in handwriting analysis, with promising applications in document processing, forensic science, and various other domains.

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