Study of Feature Fusion Methods for Document Image Classification

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***Abstract*—State-of-the-art methods for document image classification rely on visual features extracted by deep convolutional neural networks (CNNs). These methods do not use rich semantic information present in the text of the document, which can be extracted using Optical Character Recognition (OCR). In this work we study a feature fusion technique original proposed by R. Jain and C. Wigington [1]. It allows to build a model that considers both visual and textual features of a document image to perform the classification. We compare this method to other approaches for the document image classification task using the RVL-CDIP dataset [2].**

***Index Terms*—Document Image Classification, Text Classification, CNN, Transfer Learning, Feature Fusion**

I. Introduction

Automated document image classification can be a very important task in various contexts. For example can be crucial inside a document management system, to help search and information retrieval from a collection of documents. Furthermore, classify a document image could be the first important step of a Document Image Processing Pipeline, where knowing the type of document can guide the processes of information extraction.

For these reasons, many studies have been carried out on this topic. However, most of them focused on classifying the images using only their visual features, while the text contained in an image brings a lot of information about the document. Even humans in certain situations cannot distinguish between two different types of documents only looking at them, without reading the text contained in them. Therefore it seems logical to find a way to combine both visual and text features of a document to classify it. Recently, researches in this field move in this new direction and R. Jain and C. Wigington in their work ”Multimodal Document Image Classification” [1] explored various feature fusion techniques applied to the document classification task.

In this work, we want to prove the benefit of the main feature fusion method proposed by Jain and Wigington compared to pure image classifiers and pure text classifiers. Furthermore, we want to compare this method to the simpler approach to classify a document using the predictions from an image classifier and a text classifier, applying the so-called late fusion method.

In Section II we present the classification technique taken into consideration. In Section III we briefly describe the dataset used for the experiments, which are exposed in Section IV. Finally, Section V contains some conclusions of ours experiments.

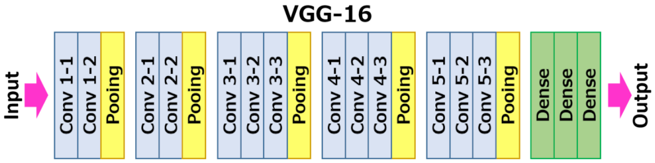

Fig. 1. The VGG16 architecture

II. Studied Techniques

A. Image Classification

Classification using the images of the documents has been the state of the art in the document classification field until recently. This approach uses a CNN to extract visual features from the document.

Various network architectures have been used over the years, but we considered the VGG16 network, as it has proven to give the best performance in this task [3].

VGG16 is a model proposed in 2014 by K. Simonyan and A. Zisserman [4] and it is composed of 16 weight layers (13 convolutional and 3 FC layers), as shown in Figure X. When it was first proposed it achieved 92.7% accuracy on the ImageNet dataset, a dataset containing millions of images belonging to 1000 classes of objects from the real world, and since then it was intensively used in computer vision tasks.

Since VGG16 takes in input 224x224 images and considering its architecture, the whole network has over 130 millions of trainable parameters. This makes training from scratch computational expensive, and it requires a huge domain-specific dataset.

It has become very popular applying transfer learning to CNN for computer vision tasks using networks pretrained on the ImageNet dataset. Even if document classification and object classification seem to be divergently domains, convolutional networks trained on the ImageNet dataset have proven to function as generalized feature extractors. In general, transfer learning has two main advantages:

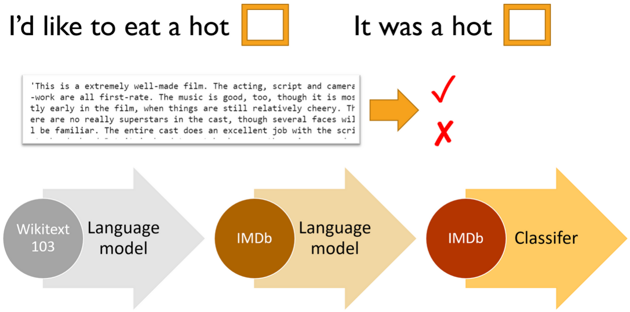
I'd like to eat a hot
It was a hot
'This is a extremely well-made film. The acting, script and camera
-work are all first-rate. The music is good, too, though it is mos
tly early in the film, when things are still relatively cheery. Th
ere are no really superstars in the cast, though several faces wil
l be familiar. The entire cast does an excellent job with the scri
✓
✗
Wikitext 103
Language model
IMDb
Language model
IMDb
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Fig. 2. **The basic steps of ULMFiT applied to a sentiment analysis problem on the IMDb dataset**: **1.** Create/download a language model pre-trained on a large corpus (e.g. the Wikitext-103 dataset). **2.** Fine-tune this language model using your target corpus. **3.** Use the fine-tuned language model to train a classifier.

- allows to achieve good performance on small datasets, for which a training process from scratch would lead to overfitting
- speedups the training process, requiring less epochs to get good results (often better than classical training approaches)

For document classification task, CNNs trained using transfer learning outperformed networks trained from scratch [3] [6].

B. *Text Classification*

Text classification has been widely studied for application like spam filtering, sentiment analysis or for topic classification. There are many methods in recent studies that used a bag of words or character followed by a traditional classifier.

These approaches are competitive for many tasks when distinctive words or special characters are sufficient for classification. For example given a text that contains words like *To: From: ecc.* it might be very probable that the text comes from a mail.

Recent researches have explored word embeddings and deep neural networks models to capture a representation of text with a good success.

There are methods like Word2Vec or GLOVE that provides tools for a semantic classification, but for our purpose we have chose another type of approach.

We have used a linguistic approach called ULMFiT *(Universal Language Model Fine-Tuning)* [5], and in Figure2 we can see its basic steps.

ULMFiT is an effective transfer learning method that can be applied to any task in NLP, and introduce techniques that are key for fine-tuning a language model and we use in our text classification for achieve large performance gains over the previous cited approaches.

The method is universal in the sense that it meets these practical criteria:

- Works across tasks varying in document size, number, and label type.
- Uses a single architecture and training process.
- Requires no custom feature engineering or pre-processing.

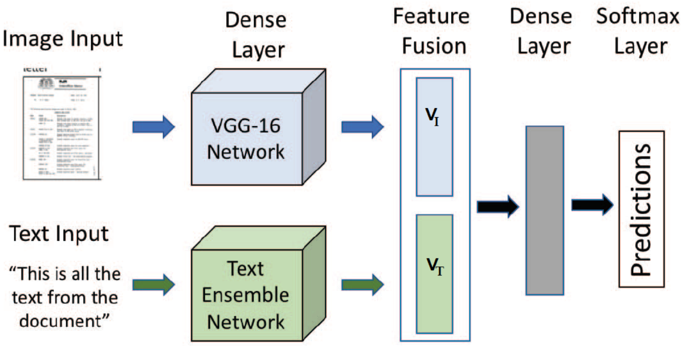


Fig. 3. A schematic representation of the feature fusion technique.

- Does not require additional in-domain documents or labels.

In fact in our experiments we have extract the text for the text classification from the image of RVL-CDIP sub-dataset that we have used for experiments, this extraction uses OCR and its explained in Section III.

C. *Multimodal Feature Fusion*

The multimodal feature fusion approach aims to perform the classification combining the feature vector representations of both the visual (V_I) and text (V_T) modalities. This approach belongs to the so-called multimodal early fusion techniques, which combine the feature representations of the different modalities.

R. Jain and C. Wigington in [1] proposed a multimodal feature fusion method for document classification. The outputs from the second-last layer of both a VGG16 and a text classifier (i.e. excluding the softmax layers) are concatenated together and sent as input to a linear layer followed by a softmax to perform the classification. The architecture of the resulting network is shown in Figure 3.

D. *Multimodal Late Fusion*

As a comparison for the performance of the multimodal feature fusion method, we also considered a multimodal late fusion technique. As opposed to early fusion ones, late fusion techniques combine the predictions of several classifiers from each modality.

In our case, we choose a very simple one: we concatenated the probabilities given by the last softmax layers of both the text and image classifiers and we gave them as input to a dense classifier, composed simply by a linear layer and a softmax.

III. Dataset and Preprocessing

We used the RVL-CDIP dataset for our experiments [10]. This collection contains 400.000 grayscale images in 16 classes, 25.000 images for each class. The dataset comes already split into 320.000 training images, 40.000 validation images and 40.000 test images. However, due to computational resources and time limitations, we created and used a mini-dataset containing only 4.000 images, preserving the proportions described above.

To train the VGG16 we resized all images to its expected input (224x224), ignoring the aspect ratios.

Concerning the text classifier, we created a textual dataset starting from the images. This textual dataset consists of a *csv* file with two columns: one containing the text read from an image and the second one containing the class label associated to that image. We used Tesseract OCR, one of the most famous open source OCR tools developed by Google, to read the text contained in each image.

We applied a preprocess step to the extracted text in which we removed the stop words. We used the list of stop words provided by NLTK, a toolkit used for NLP tasks. It is common to remove this stop words in NLP tasks so that more focus can be given to those words which contains more information about the meaning of the text.

Finally, we observed that sometimes the OCR system could not recognize any character in the image, such as for file folder documents where the image consists of a scan of the dossier, without any readable text. In these cases, we populated the text with a special character to let the text classifier work.

IV. Experiments and Results

In the following subsections, we are going to describe the performed experiments. Further implementation details and information about how to reproduce our results can be found in the Appendix.

We first trained the image and the text classifier separately, then we used them to build and train the fusion models. Table I contains the results of the studied techniques on our mini-dataset test set. The Table contains also the results obtained by the authors of [1] using the same techniques on the entire RVL-CDIP dataset.

TABLE I
Comparison between the accuracy obtained by each method on our mini-dataset and the accuracies found on the entire RVL-CDIP dataset by Jain and Wigington [1]

Method	Accuracy (Ours)	Accuracy (Reference)
Image Class.	71.88	91.10
Text Class.	60.94	85.80
Feature Fusion	**76.38**	**93.5**
Late Fusion	75.52	-

A. Image Classification

For the image classifier, we used a VGG16 pretrained with the ImageNet weights and we replaced the fully connected part appropriately. We first trained only this last part from scratch, freezing the convolutional layers. We also used a heuristic technique to choose a good learning rate without having to run multiple training. We then applied a fine-tuning process, unfreezing the convolutional part and training the whole network. During the fine-tuning, we trained each layer with a different learning rate, greater for the last layers and lower for the first ones. It is common to follow this practice to do not make the network forget what it learned from the pre-training process once unfrozen all layers. Both training processes have been done using the 1-cycle policy, first presented by Leslie Smith [8] [9], for a maximum of 75 cycles, monitoring the validation accuracy and saving the best model. The VGG16 image classifier achieved 71.88% accuracy on our mini-dataset.

B. Text Classification

The text classifier training using ULMFiT consists of three phases. In the first one, we retrieved a language model pre-trained on the Wikitext-103 dataset [11]. It is a collection of over 100 million tokens extracted from the set of verified Good and Featured articles on Wikipedia, widely used for language modeling. Then we fine-tuned the language model using our textual dataset. Finally, we used the resulting language model to build and train an AWD-LSTM textual classifier.

The training process has been made with the same modalities used for the image classifier, and the trained textual classifier obtained 60.94% accuracy.

C. Multimodal Feature Fusion

We took the two trained models just described, we removed their last softmax layers and we used them to build the multimodal feature fusion classifier, as explained in Section II-C. In order to perform the training of this new network, we concatenated also the visual and the textual datasets, to send to the network a single tensor containing the image and the text extracted from that image and preprocessed. Once again, we trained from scratch only the last FC part keeping frozen the rest of the layers. Then we fine-tuned the whole network using a different learning rate for each layer. The accuracy gain was remarkable, obtaining 76.38%.

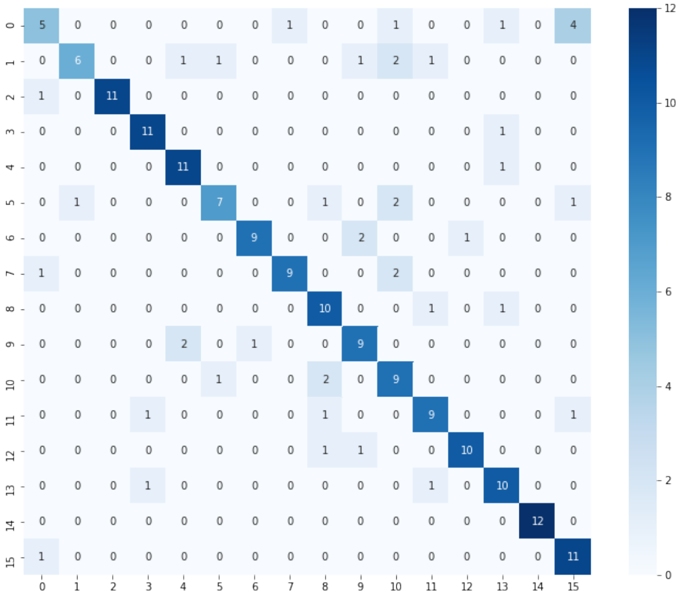
D. Multimodal Late Fusion

In the last experiment, we took our trained image and text classifiers as they were and we connected their output layer as described in Section II-D to build the multimodal late fusion model. This time made no sense to apply the fine-tuning process since in the late fusion approach we try to classify using only the predictions of classifiers from different modalities. Hence we only trained the new fully connected part, freezing the layers belonging to the image and text classifiers.

The multimodal late fusion model obtained 75.52% accuracy on the mini-dataset.

V. Conclusions

The feature fusion method proposed by Jain and Wigington in [1] is undoubtedly a sophisticated and smart technique. Considering the results in Table I, our experiments confirmed that the feature fusion allows to considerably improve the classification accuracy with respect to the classifiers using only the visual or the text features. Also the late fusion approach brings an important improvement compared to the two simple classifiers. However, with its simplicity cannot reach the feature fusion accuracy performance. Figure V contains the predictions of the four considered techniques on some example



	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	5	0	0	0	0	0	0	1	0	0	1	0	0	1	0	4
1	0	6	0	0	1	1	0	0	0	1	2	1	0	0	0	0
2	1	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	11	0	0	0	0	0	0	0	0	0	1	0	0
4	0	0	0	0	11	0	0	0	0	0	0	0	0	1	0	0
5	0	1	0	0	0	7	0	0	1	0	2	0	0	0	0	1
6	0	0	0	0	0	0	9	0	0	2	0	0	1	0	0	0
7	1	0	0	0	0	0	0	9	0	0	2	0	0	0	0	0
8	0	0	0	0	0	0	0	0	10	0	0	1	0	1	0	0
9	0	0	0	0	2	0	1	0	0	9	0	0	0	0	0	0
10	0	0	0	0	0	1	0	0	2	0	9	0	0	0	0	0
11	0	0	0	1	0	0	0	0	1	0	0	9	0	0	0	1
12	0	0	0	0	0	0	0	0	1	1	0	0	10	0	0	0
13	0	0	0	1	0	0	0	0	0	0	0	1	0	10	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0
15	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11

Fig. 4. Confusion matrix of ours Features Fusion experiments

images. Here the feature fusion clearly exploit the best of the image classifier and the text classifier to give the correct classification.

Our accuracies are much less than the reference ones, however this is expected. In Figure 4 the confusion matrix of the feature fusion model is shown. We can observe that the most confuses classes are only three (0: letter, 1: form and 5: scientific report). Recalling that our mini-dataset test set contained only 192 images, as opposed to the 40.000 images in the entire RVL-CDIP test set, we can reasonably think that with a larger dataset the accuracy would be higher and in line with the reference values.

Appendix - Implementation Details

We developed this work using the Google Colab platform. Colab provided us a powerful GPU for free to perform the experiments. We had to upload the dataset into our Google Drive the make it available to the Colab notebooks. However, due to some limitations of Colab, it was prohibitive to use the entire RVL-CDIP, so we decided to create a mini-dataset locally on our machine and work with it. For this project, we used Python 3.6 and fast.ai [12] as the main library. fast.ai is a high-level machine learning library based on PyTorch. The main advantages of this library are that it abstracts a lot of implementation details to the user and it is faster compared to other high-level machine learning libraries. Furthermore, we chose fast.ai because at the time of writing it is the only library that contains an implementation of the ULMFiT process: indeed the authors of ULMFiT and fast.ai are the same.

We used the implementation of the VGG16, the language model and the ULMFiT tools provided by the library to develop and train the image and the text classifiers. Concerning the feature fusion classifier and the late fusion one, we had to create custom models and a custom representation of the dataset to be input to the networks that concatenated the visual and textual datasets. fast.ai works very well with standard networks, but advanced tasks can be difficult to implement due to its abstraction level and the lack of documentation.

The project can be found at this GitHub repository.

References

[1] R. Jain and C. Wigington, ”Multimodal Document Image Classification”, 2019 International Conference on Document Analysis and Recognition (ICDAR), Sydney, Australia, 2019, pp. 71-77, doi: 10.1109/ICDAR.2019.00021.

[2] The RVL-CDIP Dataset, Adam W. Harley, Alex Ufkes, and Konstantinos G. Derpanis, Url: https://www.cs.cmu.edu/ aharley/rvl-cdip/

[3] M. Z. Afzal, A. K ¨olsch, S. Ahmed, and M. Liwicki, “Cutting the error by half: Investigation of very deep cnn and advanced training strategies for document image classification”, 2017.

[4] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. In ICLR, 2015.

[5] J. Howard and S. Ruder. Universal language model fine-tuning for text classification. Association for Computational Linguistics (ACL), 2018.

[6] A. Das et al., “Document Image Classification with IntraDomain Transfer Learning and Stacked Generalization of Deep Convolutional Neural Networks,” in ICPR, Aug. 2018.

[7] A Comprehensive guide to Fine-tuning Deep Learning Models in Keras (Part I): https://flyyufelix.github.io/2016/10/03/fine-tuning-in-keras-part1.html

[8] Leslie N. Smith. A disciplined approach to neural network hyper-parameters: Part 1 – learning rate, batch size, momentum, and weight decay. arXiv preprint arXiv:1803.09820, 2018.

[9] https://sgugger.github.io/the-1cycle-policy.html

[10] A. W. Harley, A. Ufkes, K. G. Derpanis, ”Evaluation of Deep Convolutional Nets for Document Image Classification and Retrieval,” in ICDAR, 2015

[11] Stephen Merity, Caiming Xiong, James Bradbury, and Richard Socher, ”Pointer sentinel mixture models”, 2016.

[12] https://www.fast.ai/

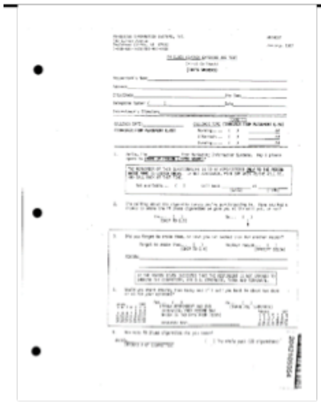
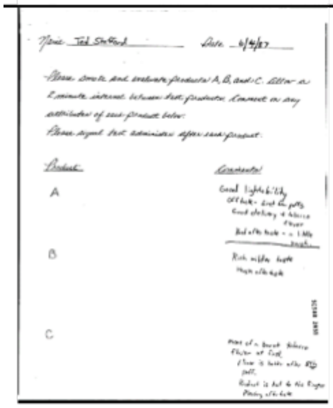
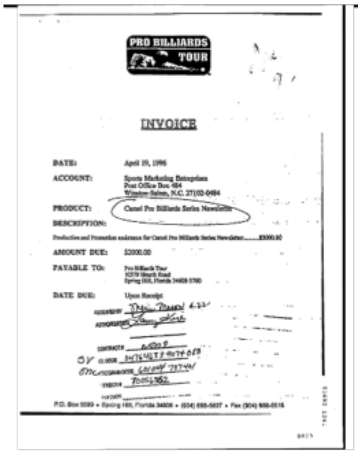
Document Image	OCR Text	Ground Truth	Predicted Classes
	2, Lim calling about the cfoarette survey you've participating in, Have you had @ … CALLBACK AY: 5. How many PM Blues cigarettes dtd you snake? 8/45 () The whote pack (20 cigar	**questionnaire**	Image: handwritten **Text: questionnaire** **Feature Fusion: questionnaire** **Late Fusion: questionnaire**
	'PHILIP MORRIS U.S.A. To: FROM: SUBJECT: INTER-OFFICE CORRESPONDENCE 120 PARK AVENUE, NEW YORK ……..	**email**	Image: memo **Text: email** **Feature Fusion: email** **Late Fusion: email**
	lame. Ted Steed thie 6] %#)e7 2 pninute antinnel betwetn Heat Prootietia, Armament ov any OM acted Of tack, (PAodtiuck: belaw … B Rich milder deste Hecch a Aer tes de ….	**handwritten**	**Image: handwritten** Text: questionnaire **Feature Fusion: handwritten** **Late Fusion: handwritten**
	DATE: April 19, 1996 ACCOUNT: Sports Marketing Enterprises Post Office Box 484 PRODUCT: , DESCRIPTION: … — . commer BADD Ee SY ace ore 33 014 088 ~ Or resrroenmncone_0/ OF T3761 ee 'ome 10050262. _—	**invoice**	Image: file folder **Text: invoice** **Feature Fusion: invoice** Late Fusion: budget

Fig. 5. Examples of images from the RVL-CDIP sub dataset extracted where the image and text classifiers predicted wrong but the feature fusion and the late fusion model did well instead.