# MULTIMEDIA SENTIMENT ANALYSIS USING MODIFIED CNN AND RNN MODELS

By

**Youssef Saad Ghatas**

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the
Requirements for the Degree of
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**in**
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**Title of Thesis:**

Multimedia Sentiment Analysis using Modified CNN and RNN Models


**Key Words:**

Multimedia Sentiment Analysis; RNN; CNN; Machine Learning



**Summary:**
Multimedia Sentiment Analysis is considered a great challenge, given the diversity of data it combines and the informality challenges it produces. Firstly, this study divides the problem into textual and visual fields and study the effect of using different CNN and RNN models. Secondly, the proposed model is compared to the top candidate and the state-of-the-art model. The proposed model -which uses deep CNN model for images and RCNN model for texts- outperforms the other tested models and the state-of-the-art model on the same dataset in both accuracy and F1 score with absolute improvement of about 5% and relative error improvement of more than 25%. Finally, a sensitivity test is conducted to test the effect of different values for some important parameters of the proposed model.

# Acknowledgements

I would like to thank Dr. Elsayed Hemayed and Dr. Mohamed Aly for their support, advice and guiding throughout the thesis. I would like to thank Dina Tantawy for her continuous encouragement and help. Finally, I would like to express my sincere gratitude to Quanzeng You for providing us with a copy of his dataset.

# Dedication

This thesis is dedicated to the soul of the dearest friend Michael Wagdy. You are truly missed... never forgotten. Thanks for all your encouragement.

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# List of Symbols and Abbreviations

| | |
|---|---|
| ANP | Adjective Noun Pair |
| BoW | Bag of Words |
| CCR | Cross-modality Consistent Regression |
| CNN | Convolutional Neural Network |
| CRNN | Convolutional-Recurrent Neural Network |
| FC | Fully Connected Layer. |
| FID | Flickr Image Dataset |
| FN | False Negative |
| FP | False Positive |
| GRU | Gated Recurrent Unit |
| HSV | Hue, Saturation, Value |
| LSTM | Long Short Term Memory |
| NLP | Natural Language Processing |
| NN | Neural Network |
| PReLU | Parametric Rectified Linear Unit |
| RCNN | Recurrent-Convolutional Neural Network |
| ReLU | Rectified Linear Unit |
| RNN | Recurrent Neural Network |
| SVM | Support Vector Machine |
| TCD | Twitter Combined Dataset |
| TN | True Negative |
| TP | True Positive |
| TTD | Twitter Text Dataset |

# Abstract

Retrieving the emotional effect of images or texts is very important to be able to handle the published content on the internet. It can be used for product selection, politics and public opinion statistics.

In spite that a lot of efforts have been made to address textual and visual ordinary classification problems, much less efforts have targeted multimedia sentiment analysis. Traditional studies of sentiment analysis targeted either images or texts, yet, it is inadequate in the era of social multimedia. It doesn't only limit the scope of the targeted content, but it also neglects the way our human brain works to combine different data. Multimedia sentiment analysis is considered a challenging task due to its high level of classification, in addition to the informalities from which the social media content suffers.

In this study, we address this problem on Twitter social multimedia content that contains both textual and visual data. We present an end-to-end complete neural network model to solve the problem of multimedia sentiment analysis. Firstly, we introduce a deep Convolutional Neural Network (CNN) for visual sentiment analysis. We compare it to the state-of-the-art model for sentiment analysis of Twitter's images. Secondly, a modified Recurrent Neural Network (RCNN) -which uses both convolutional and recurrent layers- is proposed for textual sentiment analysis. It is compared to multiple variations to test the effect of different architectures on the model. In these tests, we test two recurrent layers, namely, Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) and we test adding a convolutional layer before and after the recurrent layer.

To handle the mixed inputs of images and texts we test early-fusion and late-fusion between the two proposed models and we also test the effect of fine-tuning.

To test the effect of different values for the parameters, we conduct a sensitivity test for the proposed text model which shows the robustness of the proposed model. It also shows that the chosen parameters are enough for the models' capacity.

Finally, we analyze the proposed model using different test samples to show its points of strength and limitations. In comparison to the state-of-the-art model, the proposed model shows superior performance with absolute improvement of 5% and relative error improvement of 25% on the same test set.

# Chapter 1: Introduction

Online social networks have gained a lot of importance in our daily life. Twitter, Facebook and other social media channels have become the major sources of information, news and opinions. Most users find it a secure way to express themselves freely. Over the time, it became an expressive and unbiased way to extract opinions about different topics. It has a wide variety of applications. For example:

1. Product Selection based on the reviews of customers: the reviews of customers are used to estimate the acceptance or refusal of a product [10].

2. Predicting the results of elections: which can be used by different parties to modify their vision according to the opinions of the people [4].

## 1.1 Motivation

Retrieving sentiment analysis for social media content is considered a difficult task because it is a high level classification problem. In addition to that:

1. The same input -whether an image or a text- can have multiple meanings given different environments and events.

2. Social media data suffers from informality.

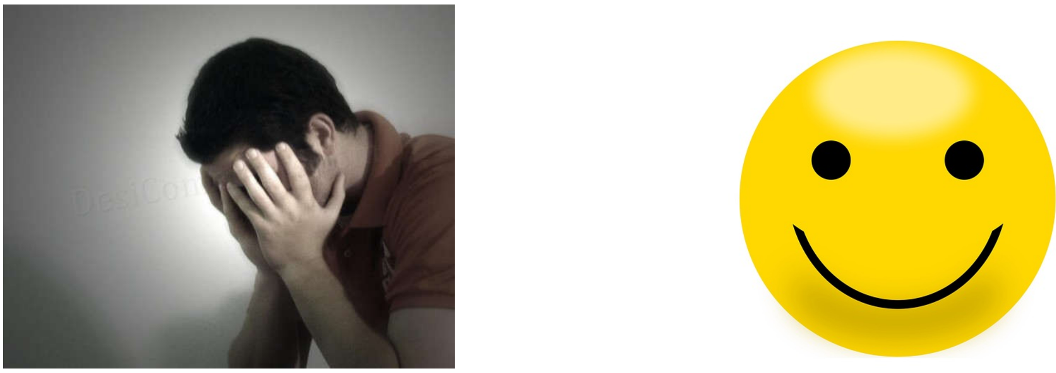
3. Images may be very different in size and quality.

4. Texts may contain non-traditional English words and abbreviations.

Textual sentiment analysis alone has become inadequate due to the variety of forms that social networks provide for users to express themselves. Accompanied with other forms of media such as images, it's more likely to be able to express and convey people's subtle feelings. For example, two extreme examples are illustrated to show the importance of using both text and image data. In figures 1.1a and 1.1b, text alone is useless, however, it's very easy to get the sentiment using the images. In contrast, in figures 1.2a and 1.2b, sentiment depends mainly on the text as it's more illustrative.

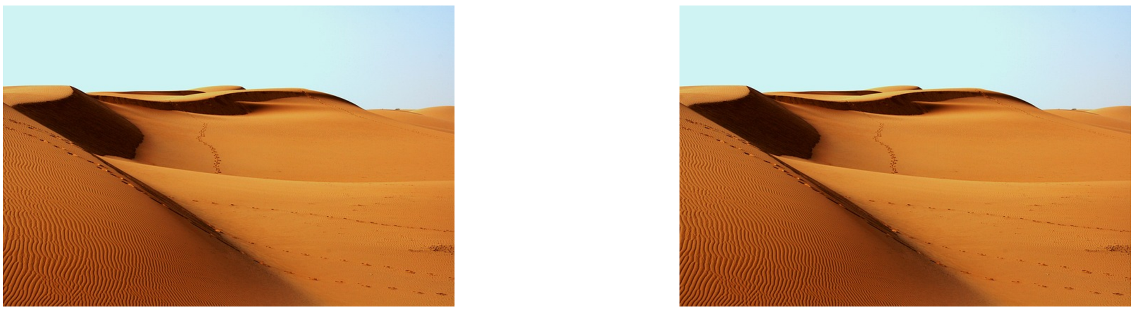
Convolutional Neural Networks (CNNs) have dominated a lot of image classification and recognition problems. They achieve state-of-the-art results in an increasing number of computer vision tasks including: scene classification [8], face recognition [1] and face detection [28].

Recurrent Neural Networks (RNNs) are appropriate for sequence problems, where the output relies on some sequence(s) of inputs. Instead of dealing with fixed-size inputs to get fixed-size outputs, they deal with variable size of sequences and relate it to one or more outputs. That's why RNNs have been used thoroughly in solving the problems of sequences including text classification [25], text completion [43], question answering[16] and speech recognition [13].



(a) “My feeling right now...” (b) “My feeling right now...”

Figure 1.1: Ambiguous text



(a) “Feeling lost :(” (b) “A great journey to the desert, loved it <3”

Figure 1.2: Ambiguous image