QUARC: Quaternion Multi-Modal Fusion Architecture For Hate Speech Classification

Deepak Kumar∗†, Nalin Kumar‡, and Subhankar Mishra§
School of Computer Sciences, NISER, Bhubaneswar 752050, India
Homi Bhabha National Institute, Training School Complex, Anushakti Nagar, Mumbai 400094, India
Email: [†deepak.kumar, §nalin.kumar, ¶smishra]@niser.ac.in

Abstract—Hate speech, quite common in the age of social media, at times harmless but can also cause mental trauma to someone or even riots in communities. Image of a religious symbol with derogatory comment or video of a man abusing a particular community, all become hate speech with its every modality (such as text, image, and audio) contributing towards it. Models based on a particular modality of hate speech post on social media are not useful; rather, we need models like multi-modal fusion models that consider both image and text while classifying hate speech. Text-image fusion models are heavily parameterized, hence we propose a quaternion neural network-based model having additional fusion components for each pair of modalities. The Model is tested on the MMHS150K twitter dataset for hate speech classification. The model shows an almost 75% reduction in parameters and also benefits us in terms of storage space and training time while being on par in terms of performance as compared to its real counterpart.

Index Terms—Quaternion algebra, Text-image fusion, MMHS150K, Hate speech, Octonion

I. INTRODUCTION

Internet, social media, in particular, make a large and integral part of our society. Laws of civilized society apply there too but a certain sense of anonymity on social media brings the worst in many people. This results in incidents of hate speech in terms of online posts on social media. Hence, some moderation system is required to identify what can be classified as hate speech. To name a few websites doing such moderation are Facebook and Reddit. Due to volume, variety, and velocity of social media content, it renders human moderators useless, leading to the need for machine moderators (using machine learning).

Existing hate speech detection models in the text have achieved significant accuracy using standard architectures like SVM, MLP, DNN. However, indirect comments with some context can also be considered as hate speech. Also, with the rise of memes and emojis, hate speeches have become quite diverse and with it, the need for investigation in machine learning-based models for hate speech detection in images arises. Hence, one needs to consider all aspects of a social media post. However, such models could easily have parameters in millions, which poses its own difficulties in terms of practical deployment. This brings us to quaternion algebra, an extension of complex algebra. Recently its use in deep neural network has shown faster convergence and reduced parameters. This rekindled interest in its possible application in machine learning. Quaternion neural networks have recently been considered in natural language processing (NLP) tasks especially because of their ability to reduce parameters by 75%.

This paper introduces multi-modal fusion model of image, text, and text of image for hate speech classification. The model achieves almost 75% reduction in parameters and also benefits us in terms of storage space and training time while being at par in terms of performance as compared to its real counterpart.

The main contributions of our paper are as follows:

- Novel quaternion multi-modal fusion model for hate speech classification.
- Almost 75% reduction in parameter size (hence, requires lesser storage space) of multi-modal fusion model as compared to current state of art.
- At par performance of quaternion multi-modal fusion model in comparison to its real counterpart.

II. RELATED WORKS

Hate speech classification has been of interest for almost three decades. One of the earliest works in the hate speech domain was Ellen Spertus’s Smokey, which classified private messages between two parties using a tree-based classifier. This paper used a rigid set of rules to create the feature vector. This model had several limitations, like, it could not handle unusual typography, grammatical mistakes or sarcasm. Though its performance was at par with that of human annotators’ but what constitutes hate speech was also quite restrictive there.

Web2.0 (The social media) using SVM classifier public forum chats. This model, in addition to the rule-based features as in Smokey, also has sentiment and context features. Provides an extensive review of hate speech classification literature in

* Authors have equal contribution
terms of the NLP task and presents different data-sets available & different approaches to the problem.

With the ease of sharing different types of content over social media the modalities of hate speech also increased. One prominent example can be memes and emojis which contain image, text in the image, whose investigation requires a new approach as presented in [15] which simply concatenated the different modalities. Another interesting work in multi-modal area is the tensor fusion network, a novel model for multi-modal sentiment analysis given by [8] exploring inter and intra-modality associations. This model observed video data giving text, image, and audio modalities and fused them using vector product of all three. Further improvement was the inter-modal sentiment analysis using attention architecture over the tensor fusion approach by [9]. In state-of-the-art [4], the authors proposed a series of multi-modal fusion models based on CNN, ResNet, and attention for hate speech classification on the Facebook data set. They claimed that an additional fusion vector improved accuracy. However, the number of parameters involved in the fusion model was too high.

Quaternion neural networks have been in computer science for quite some time in fields like signal processing and computer vision. Recently, using the quaternion transformer model [2], the authors showed that for almost all NLP tasks, quaternion model reduced 75% parameters without any significant loss in accuracy. The reason was claimed to be the Hamilton product in quaternion algebra which is the counterpart of the dot product in real algebra. [3] proposed QCNN, quaternion weight initialization, and batch normalization scheme. They experimented over the image dataset and showed that the quaternion model performed at par with the real model while reducing parameters and converging faster.

III. METHODOLOGY

We propose QUARC-a QUaternion multi-modal fusion AR-chitecture, which uses the QCNN [3] as the baseline architecture for all text, image and fusion part of model. Overall structure of our model is shown in Figure 1.

A. Text

This text model is inspired by [10], where CNN was used for sentence classification. There are two types of text, tweet text and image text. Text model is same for both but are trained separately as follows.

1) Firstly, to process the text before generating the word embeddings, we proceed as follows:
   - We removed URLs and associated symbols.
   - as it contain considerable amount of emojis, they are changed in text.

2) Then we retrieve pre-trained embeddings from GloVe [11] for tweet as well as image texts. Words not present in GloVe embeddings are set randomly. As data-set is not large enough, we don’t train GloVe word embedding model [1]. We get vectors $v_{t,x}$ & $v_{t,p}$ for tweet text and image text respectively after proper padding with word limit to be 150 per input text.

3) Then we apply quaternion 1-D convolution layer with same padding to keep input and output length same for applying quaternion attention in additional fusion.

4) After that we apply max-pooling, ReLu and flatten it.

5) Lastly, the resulting vector representation $T_t$ (tweet text) & $T_p$ (image text) (see Fig.1) obtained after applying quaternion multi-layer perceptron (Q-MLP) and a dropout layer, is used in final concatenation.

B. Image

The image model is trained as follows:

1) First we resize the images in $32 \times 32$ pixels. Now we make sure all images are 3-channeled, if not, we convert them into it by adding null channels.

2) These input images are passed through pre-trained ResNet50 without its output layer.
3) The vector \((p')\) finally obtained after passing the max pooled output \((p)\) through quaternion dense layer and dropout layer is used in final concatenation.

**C. Fusion**

1) **Simple fusion:** Here we simply concatenate \(T_t\), \(T_p\) and \(p'\). Then we apply dropout, MLP and softmax on \(concat(T_t, T_p, p')\) for the final hate speech classification.

2) **Symmetric gated fusion:** We follow the symmetric gated summation approach similar to \([12]\) and \([4]\).

In \(gated\_sum(a, p)\), we linearly transform the input vectors \(a\) & \(p\) such that they both have the same dimension. Then, we calculate \(\beta_a, \beta_p\) & \(m\) as given in the equ. \([1]\), \([2]\) & \([3]\), where the weight & bias vectors \((W_a, U_a, W_p, U_p, W_m, U_m, B_a, B_p, B_m)\) are to be learned by the model. The visual modulation gate \((f)\), as referred by \([12]\), can dynamically control the combination of text and image information.

\[
\begin{align*}
a' &= W_a \cdot a + b_a \\
p' &= W_p \cdot p + b_p \\
\beta_a &= \sigma(W_a \cdot a' + U_a \cdot p' + B_a) \\
\beta_p &= \sigma(W_p \cdot a' + U_p \cdot p' + B_p) \\
m &= \tanh(W_m \ast a' + U_m \ast p' + B_m) \\
gated\_sum(a, p) &= f = \beta_a \ast a' + \beta_p \ast m
\end{align*}
\]

Using the quaternion attention architecture \(\([2]\)\), we try to find how much the given photo information (query vector) is related to the certain part of the text (context vectors). The explicit equation for the attention is given in the equ. \([4]\). The weighted sum \(a_c\) of the text vectors, using the photo information, is then passed through the above \(gated\_sum()\) function along with the image vector \(p\).

\[
s_{c_i} = softmax(c_i^T \cdot W_a \otimes p') \quad i = 1, ..., n
\]

\[
a_c = \sum(s_{c_i} \ast c_i)
\]

where \(c = [c_1, ..., c_n]\) is the text \((t_p = \text{image text} / t_i = \text{tweet text})\) vector obtained in \([3.3.3]\).

The resultant vectors \(a_t, a_{t_w}, a_{t_{w'}}\) are then passed through the \(gated\_sum()\) along with the image vector \(p\) (where, \(a_{t_{w'}} = a_t + a_{t_p}\)). We now concatenate the vectors \(T_t, T_p, p'\), \(gated\_sum(a_t, p), gated\_sum(a_{t_w}, p)\& gated\_sum(a_{t_{w'}}, p)\) and apply QMLP, dropout & softmax for hate speech classification.

**D. Models**

So in summary, here are the fusion models with left side of equality denoting model with its input and right side of equality giving concatenation layer with its input which is then followed by dropout, quaternion dense layer and softmax operations for the final hate speech classification.

**Model 1:**

\[
F(v_t, v_p, \text{strip}) = C(T_t, T_p, p', GS(a_t, p), GS(a_{t_w}, p), GS(a_{t_{w'}}, p))
\]

**Model 2:**

\[
F(v_t, v_p) = C(T_t, T_p, p', GS(a_t, p))
\]

**Model 3:**

\[
F(v_p, \text{strip}) = C(T_t, T_p, p', GS(a_t, p))
\]

**Model 4:**

\[
F(\text{strip}, v_t, v_p) = C(T_t, T_p, p', GS(a_t, p), GS(a_{t_w}, p))
\]

**Model 5:**

\[
\text{simpleconcat}(v_t, v_p) = C(T_t, T_p, p')
\]

**Model 6:**

\[
v_t = C(T_t)
\]

**Model 7:**

\[v_p = C(p')\]

Here \(F\) represents fusion, \(C\) represents concat, \(GS\) represents \(gated\_sum\)

**IV. EXPERIMENTS**

**A. Data**

We did an experiment on the only publicly available dataset having both image and text that we could gather, which is MMHS150K \([1]\) twitter data-set for hate speech. It is a manually annotated data comprising 150,000 twitter tweets, each containing a tweet text component (may contain emojis, and URL), a tweet image component and may also contain image text component (text extracted from tweet image using Google Vision API). Figure 2 shows few sample images with corresponding tweet text as its caption. Out of this validation set contains 5,000 and test set 10,000 tweets. Our code is available at \url{https://github.com/smlab-niser/quaternionFusion}.

**B. Hyper-parameters**

We use 100-dimensional twitter GloVe embeddings, which are trained on 2B tweets, making it suitable for our experiment. Maximum word length is set to 150 for each input. We use 1D-convolution windows of size 5 with 128 filters for both image and tweet text while 2D-convolution windows of size 5 with 128 filters for both.
size $2 \times 2$ & $3 \times 3$ for image training. Dimensions of $T_t$, $T_p$ & $p$ is set to 64. Other hyper-parameters are given in Table I

### C. Results & Analysis

Results of our experiments are given in Table II. In this table, we have real and quaternion version of each model. The table shows number of trainable parameters, ROC-AUC score and average precision score for each fusion model.

In the Table II, we can see that quaternion version for each fusion model shows almost 75% reduction in trainable parameters as compared to the real one. Despite this reduction in parameters, we can see comparable performance (ROC-AUC score and average precision score) between quaternion and real. The quaternion version of $\text{fusion}(v_{t}, v_{p}, p)$ model shows best ROC-AUC score and the quaternion version of $\text{fusion}(\text{sum}(v_{t}, v_{p}), p)$ model shows best average precision score among all models.

The ROC-AUC score of $v_t$ model is slightly better than some of the fusion models, which is against our expectation. However, similar trend is seen in $v_p$. Also, we traded off performance by resizing the images in $32 \times 32$ pixels (while $v_t$ considered images of 500 pixels) because otherwise matrices corresponding to images were getting too big to be handled by our current setup. We suspect this might be the reason for information loss in image, hence, contributing less in the fusion models.

From the results of Table I, we can observe that performance isn’t improving much from only text ($T_t$) to fusion of text and image text ($T_p$) and finally fusion of all three, regarding which Table I suspects that fusion model is not able to extract information other that the text modality. However, we suspect that this can be asserted to the unique nature of this dataset and its noise because of extracted image text and the subjectivity of annotator (also mentioned in Table I). But, the improvement of performance with fusion can be seen in experiments of $v_t$ and $v_p$, which is done over Facebook dataset (not public).

### V. CONCLUSION

Social media is an important platform to bring our society together with healthy discourse. But, because of some bad apples, even this place is becoming toxic, unsafe and, a propaganda tool. Hate speech nowadays comes in the combination of image, video, audio and text. So multi-modal models become essential for hate speech classification. However, these models are having high number of parameters. In this paper we conclude that quaternion based multi-modal fusion model not only reduces parameters in comparison to its real counterpart but also achieves comparable performance because of the ability of quaternion to handle images better. These results motivate us to further look into similar model based on another such hyper-complex space, octonion algebra, an extension of quaternion algebra. Also, improvements can be made by considering video as part of posts. Further we are working on developing Qu-BERT architecture for multi-modal fusion.

### REFERENCES

[1] Gomez, R., Gibert, J., Gomez, L., & Karatzas, D. (2020). Exploring Hate Speech Detection in Multimodal Publications. In The IEEE Winter Conference on Applications of Computer Vision (pp. 1470-1478).

[2] Tay, Y. Y., Zhang, A., Tuan, L. A., Rao, J., Zhang, S., Wang, S., ... & Hui, S. C. (2019). Lightweight and efficient neural natural language processing with quaternion networks. arXiv preprint arXiv:1906.04395.

[3] Gaudet, C. J., & Maidia, A. S. (2018, July). Deep quaternion networks. In 2018 International Joint Conference on Neural Networks (IJCNN) (pp. 1-8). IEEE.

[4] Yang, F., Peng, X., Ghosh, G., Shilon, R., Ma, H., Moore, E., & Predovic, G. (2019, August). Exploring Deep Multimodal Fusion of Text and Photo for Hate Speech Classification. In Proceedings of the Third Workshop on Abusive Language Online (pp. 11-18).

[5] Spertus, E. (1997, July). Smokey: Automatic recognition of hostile messages. In AAAI/IAAI (pp. 1058-1065).

[6] Yin, D., Xue, Z., Hong, L., Davison, B. D., Kontostathis, A., & Edwards, L. (2009). Detection of harassment on web 2.0. Proceedings of the Content Analysis in the WEB, 2, 1-7.

[7] Schmidt, A., & Wiegand, M. (2017, April). A survey on hate speech detection using natural language processing. In Proceedings of the Fifth International Workshop on Natural Language Processing for Social Media (pp. 1-10).

[8] Zadeh, A., Chen, M., Poria, S., Cambria, E., & Morency, L. P. (2017). Tensor fusion network for multimodal sentiment analysis. arXiv preprint arXiv:1707.07250.

[9] Ghosal, D., Akhtar, M. S., Chauhan, D., Poria, S., Ekbal, A., & Bhattacharyya, P. (2018). Contextual inter-modal attention for multimodal sentiment analysis. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (pp. 3454-3466).

[10] Kim, Y. (2014). Convolutional neural networks for sentence classification. arXiv preprint arXiv:1408.5882.

[11] Pennington, J., Socher, R., & Manning, C. D. (2014, October). Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP) (pp. 1532-1543).

[12] Lu, D., Neves, L., Carvalho, V., Zhang, N., & Ji, H. (2018, July). Visual attention model for name tagging in multimodal social media. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (pp. 1990-1999).

[13] Sood, S., Antin, J., & Churchill, E. (2012, May). Profanity use in online communities. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (pp. 1481-1490).

[14] Al-Makhadmeh, Z., & Tolba, A. (2020). Automatic hate speech detection using killer natural language processing optimizing ensemble deep learning approach. Computing, 102(2), 501-522.

[15] Sabat, B. O., Ferrer, C. C., & Giro-i-Nieto, X. (2019). Hate Speech in Pixels: Detection of Offensive Memes towards Automatic Moderation. arXiv preprint arXiv:1910.02334.

### Table II: Performance of the proposed models

| Model No. | Model                                                                 | # Trainable Param. | ROC-AUC | Avg Precision Score |
|-----------|-----------------------------------------------------------------------|--------------------|---------|---------------------|
| 1.        | $\text{fusion}(v_{t}, v_{p}, p)$                                      | 2,810,573          | $719,837$ | $70.28$             |
| 2.        | $\text{fusion}(v_{t}, p)$                                             | 1,241,545          | $311,353$ | $70.39$             |
| 3.        | $\text{fusion}(v_{t}, p)$                                             | 1,241,545          | $311,353$ | $70.46$             |
| 4.        | $\text{fusion}(\text{sum}(v_{t}, v_{p}), p)$                         | 2,152,305          | $701,553$ | $70.03$             |
| 5.        | $\text{simpleconcat}(v_{t}, v_{p}, p)$                               | 1,219,894          | $301,361$ | $70.84$             |
| 6.        | $v_{t}$                                                              | 5,000,229          | $192,729$ | $70.80$             |
| 7.        | $v_{p}$                                                              | 1,241,201          | $32,890$  | $50.34$             |

The table shows number of trainable parameters, ROC-AUC score and average precision score for each fusion model.