VoiceMoji: A Novel On-Device Pipeline for Seamless Emoji Insertion in Dictation

Sumit Kumar  
Samsung R&D Institute  
Bangalore, India  
sumit.kr@samsung.com

Harichandana B S S  
Samsung R&D Institute  
Bangalore, India  
hari.ss@samsung.com

Himanshu Arora  
Samsung R&D Institute  
Bangalore, India  
him.arora@samsung.com

Abstract—Most of the speech recognition systems recover only words in the speech and fail to capture emotions. Users have to manually add emoji(s) in text for adding tone and making communication fun. Though there is much work done on punctuation addition on transcribed speech, the area of emotion addition is untouched. In this paper, we propose a novel on-device pipeline to enrich the voice input experience. It involves, given a blob of transcribed text, intelligently processing and identifying structure where emoji insertion makes sense. Moreover, it includes semantic text analysis to predict emoji for each of the sub-parts for which we propose a novel architecture Attention-based Char Aware (ACA) LSTM which handles Out-Of-Vocabulary (OOV) words as well. All these tasks are executed completely on-device and hence can aid on-device dictation systems. To the best of our knowledge, this is the first work that shows how to add emoji(s) in the transcribed text. We demonstrate that our components achieve comparable results to previous neural approaches for punctuation addition and emoji prediction with 80% fewer parameters. Overall, our proposed model has a very small memory footprint of a mere 4MB to suit on-device deployment.

Index Terms—Semantic analysis, Text Boundary Detection, Deep learning

I. INTRODUCTION

Speech recognition systems have been around for more than five decades with the latest systems achieving Word Error Rates (WER) of 5.5% [1] [2], owing to the advent of deep learning. Due to existing data security and privacy concerns in cloud-based ASR systems, a clear shift in preference towards on-device deployment of the state-of-the-art Automated Speech Recognition (ASR) models is emerging [3].

Gartner predicts that by 2022, 80% of smartphones shipped will have on-device AI capabilities [4]. As per a recent survey by Pericient [5] on mobile voice usage, over 19 percent of users prefer to dictate messages. However, while the world has become increasingly multimodal with chats now involving various modalities such as emojis, stickers, etc., speech recognition systems only transcribe words in the speech and remain apathetic towards such modalities. To the best of our knowledge, existing methods of adding emoji(s) to transcribed text rely on either the user interface (UI) based methods or explicit mention of emoji e.g. “fire emoji” and not on automatic insertion of emoji(s). The latter method of dictating emoji is unnatural and inadequate. Also, the user may not remember the keywords to include the specific type of emojis as per the context. There has been work done on adding multiple emojis to text directly [6] but not using transcribed text from audio input which is our main focus. In this paper, we show a system for transcribing text from the speech that automatically adds emoji(s) to the transcribed text, some samples of which are shown in Figure 1.

Fig. 1. Voicemoji output of Sample voice input from Google and Bixby voice assistants.
In the text understanding module, we predict emoji(s) for the sentence sub-part(s) and render an emoji-rich transcribed text. Emojis are used everywhere from social media to chatting apps. While speech recognition systems reduce the typing need of a user, they do not provide the user with a completely hands-off experience that these systems were originally intended for. Our system serves the user’s need of adding emotion to text, thus creating a truly hands-off experience for the user. Our contributions can be summarized as follows:

- We propose a novel on-device pipeline for adding emoji(s) in transcribed text. To the best of our knowledge, this is the first on-device system for emoji addition in transcribed text.
- We train a compact on-device emoji boundary detection model and present experimental evaluations and comparisons.
- We present a compact on-device emoji prediction model and demonstrate competitive results with 80% fewer parameters.

II. BACKGROUND

A. Sentence Boundary Detection

Recovering sentence boundaries from speech and its transcripts is a core task for speech recognition as it is essential for readability and downstream tasks. Most research focuses on using either prosodic [8] features or lexical cues [9] [10], but most state of the art results were achieved using both prosodic and lexical information [11] [12]. Recent work of [13] gives the state-of-the-art performance on predicting punctuation. They use transfer learning on pre-trained BERT embeddings [14] and train a Bi-LSTM with a linear CRF classifier on top of these embeddings. All these researches focus mainly on detecting punctuation in the transcribed text, unlike our task. For adding emoji(s) in transcribed text for emoji prediction, we require detecting sentence sub-parts as well along with sentence boundaries. Moreover, most of these works are server-based and do not focus on latency and memory, two important metrics for on-device performance evaluation.

B. Emoji Prediction

Emoji prediction is an essential feature of almost all modern keyboards. The first modern work of emoji prediction was presented with Deepmoji [15] architecture. However, despite its phenomenal accuracy in predicting emoji(s), it is too large to be deployed on-device. More recently, [16] presented a federated learning framework of predicting emoji(s) on-device, with the model trained on user data where they use CIFG. While this helps in user personalization and prediction with out-of-vocabulary (OOV) words, it presents its challenges of network availability, security breaches as showcased by [17]. The state-of-the-art (SOTA) benchmarks [18] show that BERT-based [19] models largely outperformed the other existing [15] architectures. But these models are not suitable for devices where memory footprint and response time are constrained. Recently there has been ongoing research to reduce the memory footprint of BERT [20], but still, the model size is around 100 MB and hence we do not consider the same for our evaluation. In this paper, we present a memory-efficient emoji prediction model that requires zero network usage and is completely on-device, preventing any data privacy issues. Also, we handle OOV words by the combination of character and word embeddings.

III. PROCESSING PIPELINE

Figure 2 shows an overview of the processing pipeline. The individual components in the pipeline are discussed in detail below. Since there is no open dataset to evaluate the complete pipeline: Emoji Boundary Detection + Emoji prediction on transcribed text from the audio input, the procedures described in this paper are applied to a set of over 10000 samples collected from 10 individuals’ chat annotated by 10 experts from different backgrounds and age groups to include diversity. These samples being actual user data provide a meaningful evaluation of the solution developed. Apart from this, for training and benchmarking individual modules, various open-source datasets in conjunction with our custom dataset are used, details of which are provided in the respective modules. We considered using the SemEval dataset [21]. But this includes tweets that contain one and only one

![Fig. 2. Processing Pipeline for Emoji insertion in dictation.](image-url)
emoji, whereas our main focus is to predict multiple emojis in-between as well.

A. Text Processing: Emoji Boundary Detection

The emoji boundary detection module identifies where to predict emoji(s) in a given transcribed text. For this purpose, we identify two major categories of boundaries. Emoji can either be predicted at the end of a sentence or within a sentence when a sub-part is detected.

For this task, we use CNN/DM dataset [22] for training the model. We have chosen this dataset as it has an MIT license, making it ideal for unhindered research. Though we can detect sentence boundaries by identifying punctuations of type '.', '?', etc., but we need to identify sub-parts in a sentence as well since emoji may be needed to be inserted even if there is no sentence boundary (as shown in the examples in Figure 3). We use the Open NLP part-of-speech (POS) tagger [23] to identify these sub-parts.

Our emoji boundary detection task doesn’t require all the labels in a standard POS tagger. Since our task focuses on splitting a sentence into meaningful sub-parts, we experimented with fewer tags without losing the context of the sentence. There is a list of 36 POS tags in the Penn Treebank Project [24]. For splitting a sentence into meaningful sub-parts, we recognize and use a subset of these tags for our task. We use CC (coordinating conjunction), IN (subordinating conjunction), WP (Wh-pronoun), WP$ (Possessive wh-pronoun), and WDT (Wh-determiner) tags.

Fig. 3. Sample results with and without pre-processing with POS tags.

The POS tagger is then used to prepare the CNN/DM dataset for emoji boundary detection. This involves processing the dataset using a POS tagger to determine sub-parts in the sentence. This is done as we observe that more valid boundaries get detected after using POS tagger in preprocessing as clearly shown in Figure 3 and thus improving the user experience significantly. Further, we convert each article from the resulting POS processed dataset to samples of size 6 words, as we found this to give optimal results after thorough experimentation the results of which can be seen in Figure 4. This is done by sliding the window of size 6 by one word at a time. We add padding at the start and the end of the article to make sure the boundary is predicted for the starting and ending words as well. The labels are then determined based on if there is a boundary after the 4th word of each sample. ‘True’ represents the presence of boundary and ‘False’ represents absence.

We train a CNN-based model on the processed CNN/DM dataset for emoji boundary detection with a vocabulary size of 20K. This model consists of an embedding layer (pre-trained glove embedding), 1D convolutional layer (with 512 filters, kernel size of 3, and dilated by a factor of 2), Max pooling layer with pool size 2, ‘Flatten’ layer which is then followed by a ‘Dense’ layer. We use dilated CNN as they cover a larger receptive field without loss of context, which is faster and also better performing [25]. The model architecture is shown in Figure 5.

\[
P(\text{boundary} \mid i) = \text{sigmoid}(y^{out}(i-3, i+2))
\]

\[i \in (i, \text{words})\]
### Table I

**Emoji Boundary Model Performance Evaluation**

| Model  | Embedding Dimension | Class Weight Ratio | Size      | Precision | Recall  | F1 Score | Accuracy | Multi-line Accuracy |
|--------|----------------------|--------------------|-----------|-----------|---------|----------|-----------|--------------------|
| CNN    | 100                  | NA                 | 2.15MB    | 90.77%   | 87.5%  | 89.10%   | 95.29%   | 93.37%            |
| CNN    | 50                   | NA                 | 819KB     | 90.02%   | 85.75% | 87.83%   | 94.7%    | 92.17%            |
| BiLSTM | 64                   | 0.15               | 468KB     | 68.3%    | 91.88% | 78.36%   | 88.51%   | 84.52%            |
| BiLSTM | 64                   | 0.2                | 468KB     | 73.27%   | 89.01% | 80.38%   | 90.1%    | 87.86%            |
| BiLSTM | 64                   | 0.25               | 468KB     | 74.21%   | 85.62% | 79.50%   | 90.01%   | 86.9%             |
| BiLSTM | 64                   | 0.35               | 468KB     | 62.91%   | 50.04% | 55.74%   | 82.01%   | 84.48%            |

### Table II

**Multi-sentence Validation Set Samples**

| Input Samples                                                                 |
|--------------------------------------------------------------------------------|
| I saw one amazing dress today I wanted to buy it so badly but it was so expensive now i regret not getting it |
| I dont think i can make it I am really sorry I have an important meeting with my client I will definitely come next time |
| Hey what do you have for lunch today I had ordered pizza it was delicious     |
| Today was a very busy day for me my boss gave me extra work and I had to complete by evening now i feel like going out for a drink would you like to join me |

Where $y_{out}^i$ represents the model output logits for token $i$. The boundary is predicted for the 4th word by considering the previous 3 and the next 2 words to get contextual and semantic information. The output is the probabilities for two labels: boundary present, and not present.

We use scaled loss function to train our model as follows:

$$
\text{Scaled Loss} = - \sum_{\text{batchsize}} B \{ \log(y_{out}^B) \} + \left\{ \frac{N}{M} (1 - B) \right\} (1 - y_{out}^B) \tag{2}
$$

Where $B$ is the true label for a boundary, $N$ is the number of samples with boundary, $M$ is the number of samples without boundary, and $y_{out}^B$ is the model output probability for a boundary. The training accuracy of the above model is 93.15% on CNN/DM dataset.

Table I shows the results of evaluating various architectures using the validation set (mentioned in Section III) for the task of Emoji Boundary detection. Here, multi-sentence accuracy is the accuracy calculated over test samples consisting of more than one sentence some of which are shown in Table II. Analyzing the results, we use the CNN model with embedding dimension 50 considering model size and performance. As compared to the state-of-the-art BERT-based model [13] which has a model size in hundreds of MB, our model size is just under 1MB.

To further ascertain, the efficacy of our model, we benchmarked on the DailyDialog dataset [26], shown in Table III. We extracted multi-sentence dialogues (dialogues having more than one subpart which is determined by both punctuations and POS tags) specifically, as sentences with just one subpart carry no significance for our use case. Despite the small number of parameters, our model performs well and it is noted that while our model may miss some possible boundaries, it has high precision in the ones that it predicts which is more valuable over recall for our task. Since it’s a bad user experience if the user has to correct the system offered predictions.

To deploy on-device, we convert the frozen model (of size 3.5MB) to tflite using TocoConverter [3] and reduce the size of the model using the OPTIMIZE_FOR_SIZE option. This results in a model size reduction of 75% (Final model size: 819KB). We use this model for on-device inferencing. Standalone execution of this model on-device uses 10MB of RAM and takes an inference time of $\sim$4ms for 10 words.

### B. Text Understanding: Emoji Prediction

After identifying the emoji boundary, we predict emoji(s) for each subpart. We present IdeoNet modeling which deals with semantic analysis of user text to suggest relevant emoji(s). For building semantic IdeoNet, we experimented with different classification models trained on the Twitter corpus [27].
We evaluate the approaches discussed above on the Twitter dataset (≈20K sentences) for the Emoji prediction task. Table IV shows that with ACA LSTM, we achieved comparable accuracy to DeepMoji [2] with an ≈80% lesser parameters.

IV. RESULTS

We evaluate performance both individual component-wise (explained in Section III-A and Section III-B) and of the pipeline.

To validate the complete pipeline, since there is no open dataset for this as explained in Section III, we crowdsource the validation data of 50000 chat messages. From this, the messages where emoji is used are retained, reducing the total number of messages to ≈10000. Dictation output only presents dictionary words, thus we pre-process the samples collected to remove redundant data and special characters such as digits, $, etc. Also, we remove code-switched chat messages (that consist of words from non-English language but written using English letters). We expand various chat short forms using a script. For example, “gn” is expanded to “good night”.

We use the Samsung A50 smartphone model (Android 9.0, 6GB RAM, 64GB ROM, Samsung Exynos 7 Octa9610) to experiment and measure on-device performance, the results of which are shown in Table V. Overall solution accuracy is

---

**TABLE IV**

EMOJI PREDICTION MODEL PERFORMANCE EVALUATION

| Model                  | Top 1 Accuracy | Top 5 Accuracy | F1 score | No. of parameters |
|------------------------|----------------|----------------|----------|-------------------|
| Bag of Words           | 12.5%          | 27%            | 11.20    | 3.2M              |
| LSTM (Char Embedding)  | 17.2%          | 36%            | 14.71    | 0.2M              |
| LSTM (Word Embedding)  | 18.7%          | 40.5%          | 15.89    | 4.2M              |
| ACA LSTM               | 20.1%          | 42.7%          | 16.43    | 4.3M              |
| DeepMoji               | 22.8%          | 44%            | 17.14    | 22.4M             |

---

**TABLE V**

ON-DEVICE MODEL PERFORMANCE

| Model                              | RAM (MB) | ROM (MB) | Model Initialization Time | Inference Time |
|------------------------------------|----------|----------|---------------------------|----------------|
| Emoji boundary (CNN)              | 10       | 0.819    | 10ms                      | 0.4ms/word     |
| Emoji prediction                   | 3        | 3        | 250ms                     | 0.8ms/word     |
| Emoji in Dictation Solution (CNN) | 15       | ~4       | 260ms                     | 1.25ms/word    |

---

**TABLE VI**

FUTURE ENHANCEMENTS FOR VOICEMOJI

| Input                                      | Expected Output                                      | Voicemoji Current Output                         |
|--------------------------------------------|------------------------------------------------------|--------------------------------------------------|
| because it was raining i came late to office | because it was raining [rain emoji] i came late to office [office emoji] | because it was raining i came late to office [office emoji] i came late to office [office emoji] |
| i came late to office because its was raining  | i came late to office [office emoji] because its was raining [rain emoji] | i came late to office [office emoji] because its was raining [rain emoji] |
| do you really think i am happy              | do you really think i am happy [sarcastic emoji]     | do you really think i am happy [happy emoji]     |
| yesterday is mine birthday                  | yesterday was my birthday [cake emoji]               | yesterday is mine birthday [cake emoji]         |

We explore various deep learning approaches which involve a baseline LSTM model using an attention mechanism with skip connections. Further, we optimize the baseline by analyzing the impact of parameter reduction on model performance and accuracy. However, none of the approaches yielded satisfactory accuracy due to the presence of Out of Vocabulary (OOV) words.

We propose a novel architecture **Attention-based Char Aware (ACA) LSTM** for generating a lightweight model to handle OOV words. This model uses CNN for learning char level embedding such that similar representation is learned for phonetically similar words. Also, both semantic and orthographic information is preserved by aggregating Char-level and Word representation using the attention mechanism.

The Model consists of embedding layer - size 16 (custom embedding trained along with the model with the same corpus), Convolutional layer - size 30 (Kernels: 5,10,15 of width 1,2,3 respectively), Attention Layer - size 46 (word Embedding + CNN), LSTM Layer1 (128 nodes), LSTM Layer2(128 nodes), Attention Layer - size 302 (concatenating output of Attention layer 1, LSTM Layer 1 and 2 ), Softmax class with 64 labels (Frequently used emojis) as illustrated in Figure 6.

We use the Samsung A50 smartphone model (Android 9.0, 6GB RAM, 64GB ROM, Samsung Exynos 7 Octa9610) to experiment and measure on-device performance, the results of which are shown in Table V.
calculated based on if our model predicts emoji at the correct boundary and if emoji is predicted from the same category as the one used by the user. The overall accuracy of our solution is 94%. Voicemoji has an average inference time of 7.2 ms for a 6-word sentence and a total ROM of ~4MB. Voicemoji as a library consumes only ~15 MB RAM.

Table [VI] shows details of future enhancements and some negative scenarios where our proposed system of Voicemoji fails. As clearly shown, the first example shows the system behavior comparison between two similar but rephrased inputs. As observed, in the case of the presence of ‘because’ in the middle, since our sentence boundary prediction model is trained on such scenarios with the help of POS tagging, it gives the correct output for boundaries, but in the first sentence due to sentence starting with ‘because’, it fails to predict a boundary after ‘raining’. But it is to be noted that this does not result in a completely wrong output and is acceptable. The second scenario is that incase of sarcasm. Since we haven’t integrated a sarcasm detection module, our system fails to give correct emoji predictions. This is to be improved as future work for our proposed solution. The last scenario is in the case of grammatical errors. This as well is due to the absence of a grammar correction module, which is to be explored as part of future work along with sarcasm detection.

V. CONCLUSION

We introduce a first-of-its-kind pipeline to insert emoji(s) in dictation in real-time on-device. The initial results of these procedures are promising and demonstrate how dictation can be enriched with emojis and made more fun, thus paving way for a true hands-off dictation experience. This pipeline can be easily extended for other languages, once respective building blocks are adapted for a new language. While evaluating the solution performance, a major category of failure in incorrect emoji prediction is observed due to a lack of sarcasm detection where there is a scope to improve emoji prediction.

REFERENCES

[1] G. Saon, G. Kurata, T. Sercu, K. Audhkhasi, S. Thomas, D. Dimitriadis, X. Cui, B. Ramabhadran, M. Picheny, L.-L. Lim et al., “English conversational telephone speech recognition by humans and machines,” arXiv preprint arXiv:1703.02136, 2017.

[2] W. Xiong, J. Droppo, X. Huang, F. Seide, M. Seltzer, A. Stolcke, D. Yu, and G. Zweig, “Achieving human parity in conversational speech recognition,” arXiv preprint arXiv:1610.05256, 2016.

[3] A. Mehrrotas, L. Dudiak, J. Yeo, Y.-y. Lee, R. Vipperla, M. S. Abdelfattah, S. Bhattacharya, S. Ishitaq, A. G. C. Ramos, S. Lee et al., “Iterative compression of end-to-end asr model using auotvm,” arXiv preprint arXiv:2008.02897, 2020.

[4] Gartner, “Gartner Highlights 10 Uses for AI-Powered Smartphones,” https://www.gartner.com/en/newsroom/press-releases/2018-03-20-gartner-highlights-10-uses-for-ai-powered-smartphones 2018. [Online; accessed 15-October-2020].

[5] E. Eng, “Mobile Voice Usage Trends in 2020,” https://www.perficient.com/insights/research-hub/voice-usage-trends 2020. [Online; accessed 15-October-2020].

[6] H. Jiang, A. Guo, and J. Ma, “Automatic prediction and insertion of multiple emojis in social media text,” in 2020 International Conferences on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData) and IEEE Congress on Cybernetics (Cybernetics). IEEE, 2020, pp. 505–512.

[7] A. G. Adami, R. Mihaescu, D. A. Reynolds, and J. J. Godfrey, “Modeling prosodic dynamics for speaker recognition,” in 2003 IEEE International Conference on Acoustics, Speech, and Signal Processing, 2003. Proceedings.(ICASSP’03)., vol. 4. IEEE, 2003, pp. IV–788.

[8] M. Haase, W. Kriegelbaum, G. Mohler, and G. Stenzel, “Deriving document structure from prosodic cues,” in Seventh European conference on speech communication and technology, 2001.

[9] A. Stolcke, E. Shriberg, R. Bates, M. Ostendorf, D. Hakkanli, M. Plauche, G. Tur, and Y. Lu, “Automatic detection of sentence boundaries and disfluencies based on recognized words,” in Fifth International Conference on Spoken Language Processing, 1998.

[10] F. Batista, H. Moniz, I. Trancoso, and N. Mamede, “Bilingual experiments on automatic recovery of capitalization and punctuation of automatic speech transcripts,” IEEE transactions on audio, speech, and language processing, vol. 20, no. 2, pp. 474–485, 2012.

[11] Y. Gotot and S. Renals, “Sentence boundary detection in broadcast speech transcripts,” 2000.

[12] C. Xu, L. Xie, G. Huang, X. Xiao, E. S. Cheng, and H. Li, “A deep neural network approach for sentence boundary detection in broadcast news,” in Fifteenth annual conference of the international speech communication association, 2014.

[13] K. Makhija, T.-N. Ho, and E.-S. Chng, “Transfer learning for punctuation prediction,” in 2019 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC). IEEE, 2019, pp. 268–273.

[14] Google, “TensorFlow code and pre-trained models for BERT,” [https://github.com/google-research/bert, 2018. [Online; accessed 15-January-2020].

[15] B. Felbo, A. Mislove, A. Søgaard, I. Rahwan, and S. Lehmann, “Using millions of emoji occurrences to learn any-domain representations for detecting sentiment, emotion and sarcasm,” arXiv preprint arXiv:1708.00524, 2017.

[16] S. Ramaswamy, R. Mathews, K. Rao, and F. Beaufays, “Federated learning for emoji prediction in a mobile keyboard,” arXiv preprint arXiv:1906.04329, 2019.

[17] K. Yang, T. Jiang, Y. Shi, and Z. Ding, “Federated learning via over-the-air computation,” arXiv preprint arXiv:1812.11750, 2018.

[18] W. Ma, R. Liu, L. Wang, and S. Vosoughi, “Emoji prediction: Extensions and benchmarking,” arXiv preprint arXiv:2007.07389, 2020.

[19] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “Bert: Pre-training of deep bidirectional transformers for language understanding,” arXiv preprint arXiv:1810.04805, 2018.

[20] Z. Sun, H. Yu, X. Song, R. Liu, Y. Yang, and D. Zhou, “Mobilebert: a compact task-agnostic bert for resource-limited devices,” arXiv preprint arXiv:2004.02984, 2020.

[21] F. Barbieri, J. Camacho-Collados, F. Ronzano, L. E. Anke, M. Balles- teros, V. Basile, V. Patti, and H. Saggion, “Semeval 2018 task 2: Multilingual emoji prediction,” in Proceedings of The 12th International Workshop on Semantic Evaluation, 2018, pp. 24–33.

[22] K. M. Hermann, T. Kocisky, E. Grefenstette, L. Espeholt, W. Kay, M. Suleyman, and P. Blunsom, “Teaching machines to read and comprehend,” in Advances in neural information processing systems, 2015, pp. 1693–1701.

[23] J. Baldridge, “The opennlp project,” URL: http://opennlp.apache.org/index.html [accessed 2 February 2012], p. 1, 2005.

[24] M. Marcus, B. Santorini, and M. A. Marcinkiewicz, “Building a large annotated corpus of english: The penn treebank,” 1993.

[25] F. Yu and V. Koltun, “Multi-scale context aggregation by dilated convolutions,” arXiv preprint arXiv:1511.07122, 2015.

[26] Y. Li, H. Su, X. Shen, W. Li, Z. Cao, and S. Niu, “Dualdialog: A manually labelled multi-turn dialogue dataset,” arXiv preprint arXiv:1710.03957, 2017.

[27] A. Pak and P. Paroubek, “Twitter as a corpus for sentiment analysis and opinion mining,” in LREC, vol. 10, no. 2010, 2010, pp. 1320–1326.