An Attention Based Neural Network for Code Switching Detection: English & Roman Urdu

Aizaz Hussain, Muhammad Umair Arshad
Artificial Intelligence & Machine Learning lab
National University of Computer and Emerging Sciences, FAST
Islamabad, Pakistan
{aizaz.hussain,umair.arshad}@nu.edu.pk

Abstract

Code-switching is a common phenomenon among people with diverse lingual background and is widely used on the internet for communication purposes. In this paper, we present a Recurrent Neural Network combined with the Attention Model for Language Identification in Code-Switched Data in English and low resource Roman Urdu. The attention model enables the architecture to learn the important features of the languages hence classifying the code switched data. We demonstrated our approach by comparing the results with state of the art models i.e. Hidden Markov Models, Conditional Random Field and Bidirectional LSTM. The models evaluation, using confusion matrix metrics, showed that the attention mechanism provides improved the precision and accuracy as compared to the other models.

1 Introduction

In sociolinguistics, a language is referred to as code. Using two languages to convey meaning is referred to as Code-Mixing (CM) and Code-Switching (CS). In this age of internet and information technology, information exchange has grown exponentially. People around the globe are connected through the internet and all these people have diverse lingual backgrounds. Using the support of two languages to convey meaning is a common phenomenon nowadays.

Code-Mixing is the most used method to communicate with one another on social media platforms. Code-Mixing means that in a single sentence a person uses multilingual vocabulary, grammar for the delivery of meaningful information. For example, consider a Pakistani student whose native language is Urdu but in school, the communication mode is in English. For such students to communicate it is commonly observed that they mix English with Urdu for the part they find difficult to speak in English. Code-switching is used when you have to switch to other languages to deliver messages. For example, a teacher in a class teaching a foreign language will first speak in the target language and then will make use of the native language to help students understand the meaning of the sentence.

Code switching poses a significant problem for text mining algorithms and online social platforms. These algorithms fail when it comes to multilingualism text processing. Existing tools are limited to the extraction of semantics for a single or one-to-one language transliteration. Our paper makes the following contributions: 1) We show that extraction with the use of attention model improves the accuracy 2) Code mixing language identification for low resource language i.e. English and Roman Urdu 3) We present a new public dataset to support research on code mixed language identification on Roman Urdu and English

In this paper, we propose to use the transformer-based neural network for the detection of Multilingual text in English and Urdu from the given dataset. We will compare the results of the proposed architecture with different classification models i.e. Hidden Markov Models (HMM), Conditional Random Fields (CRF), and a BiDirectional LSTM. The rest of the paper is divided into the following 4 sections. In section 1, we will discuss what related work has been done for the detection of multilingual language detection until now. In section 3, the proposed methodology will be explained in detail along with the working of pre-existing models. Section 4, explains the complete setup of the dataset, experimentations and comparison of the results. In section 5, we will finally summarize the findings of this paper.

2 Related Work

The problem of multilingual language detection from the text has been long identified for 30 years (Joshi, 1982; Naeem et al., 2020b). With the classification of multilingual text, much useful semantics
can be extracted from the text (Qamar et al.; Awan and Beg, 2021). The first step in this domain is to identify the POS tags (Nguyen and Verspoor, 2018; Majeed et al., 2020; Zahid et al., 2020) in multilingual text. From the machine learning perspective, one can view multilingual text detection as a classification problem. Machine learning algorithms have been applied to classify two or more languages (Amini et al., 2009; Naeem et al., 2020a; Beg and Beek, 2013; Uzair et al., 2019). Language identification from code mixed data for English Telugu languages showed that applying Hidden Markov Model (HMM), Support Vector Machines (SVM), and Conditional Random Field (CRF), the CRF outperformed the rest of the algorithms (Gunadapu and Mamidi, 2020). Similarly, if the context is taken into consideration with traditional machine learning models, as proposed in (Nguyen and Doğruöz, 2013), an accuracy of 98% was achieved for the Turkish and Dutch languages dataset.

Each language has different pronunciations and phonology combinations. So with the use of deep neural networks the proposition is to learn the morphemes and phonemes to predict the probability of each word belonging to a specific language. In the paper (Jurgens et al., 2017), the authors proposed to solve the multilingual language identification problem by using neural networks with the to learn the character combinations. In the ‘90s, LSTM (Hochreiter and Schmidhuber, 1997) was introduced to help preserve the context for long and short memory, which is being used in latest state preserving AI in games (Zafar et al., 2019a, 2018, 2019b). LSTM’s have been applied to many text processing problems including multilingual text detection (Samih et al., 2016) thus achieving an accuracy of 0.83 and 0.90 on MSA - Egyptian and Spanish - English languages.

Urdu is the widely spoken language in the south Asian region. Detection of sentiments from Urdu text gives very useful insights (Mehmood et al., 2019), especially in the context of local businesses. In the paper (Amjad et al., 2020), the author using machine translation between English-Urdu detects the fake news. A lot of work has been done in terms of basic language processing for Urdu i.e. Creation of benchmark resource for processing of Urdu language (Hussain, 2008; Arshad et al., 2019), POS tagging (Muaz et al., 2009), Stemming (Khan et al., 2012) etc.

Roman Urdu is a complex form of Urdu language communication. There are many inconsistencies which are hard to decipher when it comes to machine however it is easy for humans to understand the meaning of a particular word written in Roman Urdu. So the very first task needed was the correct depiction of Roman Urdu words in Urdu. Another problem with Roman Urdu is that it is also written in Roman characters which are used for English also, which makes it difficult to differentiate between multilingual text.

3 Methodology

3.1 Recurrent Neural Network:

Recurrent Neural Networks are good for processing sequential data. Text is also sequential data with a combination of many characters. RNN’s are reliable for short sequences. Considering a simple feed-forward neural network that has a single input layer, a hidden layer, and an output layer. The information is saved by adding the loop in the hidden state. This allows us to make a flow of information between different steps. The hidden state is updated with every iteration given the old hidden state as in input to the new one. The hidden state is updated on the bases of the following relation:

\[ h_t = f_W(x_t, h_{t-1}) \]  

Whereas, \( h_{t-1} \) in equation 1 represents the old state of \( h_t \) which is passed to update the knowledge of the network.

3.2 Attention Model:

The attention mechanism, Rather than building a single context vector the idea is to create shortcuts between the context vector and the entire source input. In this way only important features from the context vectors are highlighted. Suppose we have sequence \( x \) and target sequence \( y \), such that:

\[ x = [x_1, x_2, x_3, ..., x_n] \]
\[ y = [y_1, y_2, y_3, ..., y_n] \]

whereas, \( h_i = [h_i]^T, i = 1, 2, ..., n \)  

\[ h_i \] represents the hidden state in the encoder. The decoder contains the hidden state \( s_t \) as shown in eq 3 where \( t \) is the position of the output word.

\[ s_t = f(s_{t-1}, y_{t-1}, c_t) \]  

where, \( c_t = \sum_{i=1}^{n} \alpha_{t,i} h_i \)
The set of $\alpha_{t,i}$ are weights for each output for the emphasis on each source hidden state.

3.3 Recurrent Neural Network with Attention Model:

Feature Extraction:

To extract features from words we used skipgram model using Fasttext library. At first the word is passed converted in a vector of 300 dimensions using one hot encoding. A dot product between the word $w$ features and weights on $|v|$ neurons is performed. This hidden layer do not have any activation function. The output vector $H[1, N]$ is then taken dot product with $W[N, V]$ and will give vector $\vec{U}$ as output. Using softmax function the probability for each vector is calculated. The vector with the highest probability represents as the output.

Model:

We propose to combine a recurrent neural network combined with the attention model to efficiently enable the network to learn the features of each language. As explained in section 3.2, the network contains two part i.e. an encode and a decoder. The features extracted from words 3.3 are passed into the input layer. This input layer is passed into a bidirectional Recurrent Neural Network. In a bi-directional RNN the sequence is first passed in the order $S = \{s_1, s_2, s_3, ..., s_n\}$ and then in the other layer it is passed the in opposite direction $S' = \{s_n, s_{n-1}, s_{n-2}, ..., s_1\}$. The results from both the layer are then combined with dot product and then combined with the weights assigned by the attention layer. Following equation 2 the product can be formulated as:

$$h_t = [h^T_t, h_t^T]^T$$

The $h_t$ is then with the attention weights $\alpha$. The output vector is passed into the decoder where simple RNN aligns the sequence of the encoder output with $y_{t-1}$, eq 3.
Urdu and Roman Urdu tweets. The Aryan Urdu is later converted into Roman Urdu.

**Dataset Preparation:**
Since we are collecting data from Twitter. The problem with data on social media is that it is highly informal with a lot of misspellings, characters lengthening, and spelling variations. Some words are commonly used in both English and Urdu languages. Thus, these challenges make code-mixing identification a difficult task. An example of these challenges can be found in Table 1.

To prepare data the very first step we took was to normalize words. Now there were sentences, in the scrapped data, which had no spaces between them. Using the pre-scraped English and Roman Urdu datasets we split the word into a series of characters and then compared the sequence with the words in the dictionary. The maximum sequence of characters which resembles a word in the dictionary was treated as a single word unit. Figure 3 shows the process of dissecting a whole sentence into words. We performed tokenization on the sentences and then removed duplicates from the data.

**Dataset Annotation:**
The dataset is annotated into three classes i.e. English (en), Roman Urdu (ru), and rest (rs) which contains the information of punctuations or name entities. The data annotation process is done in a semi-supervised manner. When we are tackling with Roman Urdu and in this type of mixing usually every person has different formats for writing a single word. This is because there is no predefined standard for writing Urdu in the Roman version so everyone can have different combinations for characters for a single word as they deem fit.

| CM Challenges       | Examples                  |
|---------------------|---------------------------|
| Misspellings        | hat - hot (en)            |
| Character lengthening | youuuu (en)              |
|                     | kiaaa (ru)                |
| Spelling variations | thank you (thanku, tankyu) (en) |
|                     | (kia, kiya) (ru)          |
| Common words        | meh school (en, ru) jaa raha hu |

Table 1: Bilingual Code Mixing challenges in languages with examples. The en tag represents English language while ru represents Roman Urdu word.

Most of the words in this problem suffer from a character lengthening problem. To resolve this problem we can easily annotate the words written in Roman Urdu by maintaining a dictionary predefined dictionaries and with an addition to the scrapped words by reducing the characters lengthening to a single character. Hence, this technique will produce a basic form. Using this form we can simply find out other versions of the same word and annotate them. This technique also allows us to tackle the word duplication problems. For a single word, there can be many duplicates in spellings. We are not discarding the variations of spellings for a word because our goal is to pay attention to the words pronunciation representation of words in the vector space.

| Class | EN Tokens | RU Tokens |
|-------|-----------|-----------|
| Train | 0.3458    | 0.0392    |
| Dev   | 0.0494    | 0.247     |
| Test  | 0.0988    | 0.0049    |

Table 2: The table shows the numbers of data tokens splitted in order to train and test the models.

**Data Statistics:**
The dataset is randomly split into train and test parts as shown in Table 2. We can see that the English dataset exceeds the Roman Urdu dataset, but many words are used the same in both languages as shown in the example 4.

**Example:** Shampoo, Jungle, Loot, University etc.

For the English dataset at first, we used dictionary words which constitutes of 466k words.

1https://github.com/dwyl/english-words
Table 3: Dataset is the resource collected from different sources as well as the data which we scraped from Twitter. The data size is measured in millions of lines of words as per the category.

People usually use informal language in chats so we used a pre-trained chat dataset in English with about 1 Million sentences. For Roman Urdu work has been done for semantical analysis of tweets. Different datasets are publicly available on Kaggle and Github repositories. We used those datasets as well as we used scrapped data from Twitter in both Roman Urdu and English.

For Roman Urdu, we also targeted tweets in Arayan Urdu. We then converted the Aryan Urdu into Roman Urdu by simply using machine transliteration API \(^2\) from Arayan to Roman Urdu. Complete statistics about the dataset are shown in Table 3.

After pre-processing, cleaning and annotating data the total dataset contains about 0.5 M of English tokens and 0.05 M of Roman Urdu tokens.

5 Experimental Setup

For the validation of our research, we used two different systems. For data processing and collection we used a core i5 4210M CPU 2.40 GHz with 16 GB of RAM and an integrated Intel graphics card. To train our network we used a custom made AMD Ryzen\(^9\) CPU, 16 GB of dedicated CUDA enabled NVIDIA GeForce RTX Super graphics card, 16 GB of RAM, and SSD NVMe storage. We used pycharm IDE for experimentation and the operating system used was Linux mint.

5.1 Models

In this section, we will discuss some baseline models that were previously for multilingual language detection. We will then compare the accuracy of these models with the proposed model for this job.

Hidden Markov Model (HMM)

Hidden Markov Model (HMM) is used in many sequence related problems. HMM is a statistical model which works on the probability of state switching between states for against provided sequence. Let say we have set of classes \( C = \{c_1, c_2, \ldots, c_n \} \), which in our case are two i.e. en and ru. Then for \( d \) dimensional sequence \( S = \{s_1, s_2, \ldots, s_d \} \). The HMM model assigns the class to a word by calculating the forward and backward probabilities of classes along with the sequence provided as an input. The process is shown in the Figure 4.

![Figure 4: The architecture of Hidden Markov Model in which the connection with label \( a \) shows the hidden states of the model while \( b \) shows the output states.](https://www.ijunoon.com/transliteration/urdu-to-roman)

Conditional Random Field (CRF)

Conditional Random Field (CRF) also a statistical model which predicts class \( C \) for a given input of a sequence and based on the probability it assigns the class to the sequence \( S \) (Lafferty et al., 2001). The Hidden Markov Model is doing the same then how CRF is different? But CRF is a discriminative model working on the principles of conditional probability distribution while HMM is based on joint probability distribution. Figure 5 explains the working of CRF in context with bilingual word detection.

![Figure 5: Architecture of Conditional Random Field.](https://www.ijunoon.com/transliteration/urdu-to-roman)

Bidirectional LSTM

A bidirectional LSTM (Zhou et al., 2016) we have two LSTM architecture. The input sequence is first passed into the LSTM in the default sequence and for the other LSTM model, the input is passed in reverse order. The results of which are combined. The weights are assigned with the attention mechanism. The results are passed through some activation function to get some input. The process is explained on a running example in Figure 6 below.
| Models                  | Accuracy | Precision | Recall | F1 Score |
|------------------------|----------|-----------|--------|----------|
| Hidden Markov Model     | 0.85     | 0.73      | 0.81   | 0.72     |
| Conditional Random Field| 0.89     | 0.79      | 0.85   | 0.81     |
| Bi-directional LSTM     | 0.92     | 0.82      | 0.71   | 0.79     |
| Attention Model         | 0.93     | 0.87      | 0.75   | 0.84     |

Table 4: The table shows the evaluation metrics for different models we used in our paper in comparison to the attention model.

Figure 6: The architecture shows the workflow of a bidirectional LSTM. The first layer pass the sequence of features from 1 to n then the backward pass the sequence of features are passed from n to 1 then based on weight and activation function we get the output class.

6 Results

The annotated data used for experimentation can be used in many ways for multilingual analysis. We can observe the points to pay attention to which a speaker switches to the other language or what is the ratio for each language in code-switching. To evaluate language identification at the word level we use the following metrics.

We start from the basic measuring metrics for the evaluation of any classification task. This is precision, accuracy and recall. These metrics give us an overall overview of the document. It can provide useful information about the user preference of language on the internet. Finally, we will use the F1 score to evaluate the accuracy of the model as compared to previous models.

The comparison of the results between each model can be compared shown in Table 4. The datasets from different sources were combined for training purposes. A significant amount of tests was done by comparing the results. For basic machine learning-based models it showed that Conditional Random Field (CRF) outperformed Hidden Markov Model (HMM). It can be seen that F1-Score is higher for CRF than HMM.

The bidirectional LSTM gives an accuracy of 0.92. Using the attention model the accuracy moves to about 0.93 but the main comparison can be compared from the F1 score, precision and recall. It is evident by the comparison of results that the attention model outperformed the results from a bidirectional LSTM model. Using the attention layer we observed that time consumed by it was comparatively low from traditional RNN Neural Network. For a simple RNN, we faced the problem of memory full issue.

7 Conclusion

In this paper, we observed that using attention improves the results and reduce the steps of a network. Attention networks can be proved useful in handling different tasks of low resource language processing. However, the dataset for roman Urdu was overwhelmed by the English data. In the future, we can compare results by combining different datasets to see what type of data gives good results.

8 Future Work

Today we can see much work done in machine transliteration from one language to any other targeted language. As most of the internet communication is done in text code mixing is a common phenomena. We see room to contribute in the development of an architecture which does machine transliteration in terms of code mixed text. The basic idea is to take code mixed data and preserving the context of sentence translate into targeted language. This will be help full to extract useful semantics from code mixed text on internet. These semantics will be proved to be useful for the business community to improve there services based on customer reviews.

References

Hamza M Alvi, Hareem Sahar, Abdul A Bangash, and Mirza O Beg. 2017. Ensights: A tool for energy aware software development. In 2017 13th In-
Maaz Amjad, Grigori Sidorov, and Alisa Zhila. 2020. Data augmentation using machine translation for fake news detection in the urdu language. In *Proceedings of the 12th Language Resources and Evaluation Conference*, pages 2537–2542.

Muhammad Umair Arshad, Muhammad Farrukh Bashir, Adil Majeed, Waseem Shahzad, and Mirza Omer Beg. 2019. Corpus for emotion detection on roman urdu. In *2019 22nd International Multitopic Conference (INMIC)*, pages 1–6. IEEE.

Mubashar Nazar Awan and Mirza Omer Beg. 2021. Top-rank: a topicalpositionrank for extraction and classification of keyphrases in text. *Computer Speech & Language*, 65:101116.

Talha Imtiiaz Baig, Nazish Banaras, Ebad Banissi, Rafia Bashir, Mirza O Beg, Hasan Mujtaba, and Sohail Abbas. 2020. Deepdetect: detection of distributed denial of service attacks using deep learning. *The Computer Journal*, 63(7):983–994.

Abdul Ali Bangash, Hareem Sahar, and Mirza Omer Beg. 2017. A methodology for relating software structure with energy consumption. In *2017 IEEE 17th International Working Conference on Source Code Analysis and Manipulation (SCAM)*, pages 111–120. IEEE.

Mirza Beg and Peter van Beek. 2013. A constraint programming approach for integrated spatial and temporal scheduling for clustered architectures. *ACM Transactions on Embedded Computing Systems (TECS)*, 13(1):1–23.

Mirza Beg and Peter Van Beek. 2010. A graph theoretic approach to cache-conscious placement of data for direct mapped caches. In *Proceedings of the 2010 international symposium on Memory management*, pages 113–120.

Mirza O Beg, Mubashar Nazar Awan, and Syed Shahzaib Ali. 2019. Algorithmic machine learning for prediction of stock prices. In *FinTech as a Disruptive Technology for Financial Institutions*, pages 142–169. IGI Global.

Noman Dilawar, Hammad Majeed, Mirza Omer Beg, Naveed Ejaz, Khan Muhammad, Irfan Mehmood, and Yunyoung Nam. 2018. Understanding citizen issues through reviews: A step towards data informed planning in smart cities. *Applied Sciences*, 8(9):1589.

Muhammad Umer Farooq, Mirza Omer Beg, et al. 2019a. Bigdata analysis of stack overflow for energy consumption of android framework. In *2019 International Conference on Innovative Computing (ICIC)*, pages 1–9. IEEE.

Muhammad Umer Farooq, Saif Ur Rehman Khan, and Mirza Omer Beg. 2019b. Melta: A method level energy estimation technique for android development. In *2019 International Conference on Innovative Computing (ICIC)*, pages 1–10. IEEE.

Sunil Gundapu and Radhika Mamidi. 2020. Word level language identification in english telugu code mixed data. *arXiv preprint arXiv:2010.04482*.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation*, 9(8):1735–1780.

Sarmad Hussain. 2008. Resources for urdu language processing. In *Proceedings of the 6th workshop on Asian Language Resources*.

Abdul Rehman Javed, Mirza Omer Beg, Muhammad Asim, Thar Baker, and Ali Hilal Al-Bayatti. 2020a. Alphaloggger: Detecting motion-based side-channel attack using smartphone keystrokes. *Journal of Ambient Intelligence and Humanized Computing*, pages 1–14.

Abdul Rehman Javed, Muhammad Usman Sarwar, Mirza Omer Beg, Muhammad Asim, Thar Baker, and Hissam Tawfik. 2020b. A collaborative healthcare framework for shared healthcare plan with ambient intelligence. *Human-centric Computing and Information Sciences*, 10(1):1–21.

Hafiz Tayyeb Javed, Mirza Omer Beg, Hasan Mujtaba, Hammad Majeed, and Muhammad Asim. 2019. Fairness in real-time energy pricing for smart grid using unsupervised learning. *The Computer Journal*, 62(3):414–429.

Aravind K. Joshi. 1982. *Processing of sentences with intra-sentential code-switching*. In *Coling 1982: Proceedings of the Ninth International Conference on Computational Linguistics*.

David Jurgens, Yulia Tsvetkov, and Dan Jurafsky. 2017. Incorporating dialectal variability for socially equitable language identification. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 51–57.

Martin Karsten, Srinivasan Keshav, Sanjiva Prasad, and Mirza Beg. 2007. An axiomatic basis for communication. *ACM SIGCOMM Computer Communication Review*, 37(4):217–228.
Sajjad Ahmad Khan, Waqas Anwar, Usama Ijaz Bajwa, and Xuan Wang. 2012. A light weight stemmer for urdu language: a scarce resourced language. In Proceedings of the 3rd Workshop on South and Southeast Asian Natural Language Processing, pages 69–78.

Hussain S Khawaja, Mirza O Beg, and Saira Qamar. 2018. Domain specific emotion lexicon expansion. In 2018 14th International Conference on Emerging Technologies (ICET), pages 1–5. IEEE.

John Lafferty, Andrew McCallum, and Fernando CN Pereira. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data.

Adil Majeed, Hasan Mujtaba, and Mirza Omer Beg. 2020. Emotion detection in roman urdu text using machine learning. In Proceedings of the 35th IEEE/ACM International Conference on Automated Software Engineering Workshops, pages 125–130.

Khawar Mehmood, Daryl Essam, Kamran Shaﬁ, and Muhammad Kamran Malik. 2019. Sentiment analysis for a resource poor language—roman urdu. ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP), 19(1):1–15.

Ahmed Muaz, Aasim Ali, and Sarmad Hussain. 2009. Analysis and development of urdu pos tagged corpus. In Proceedings of the 7th Workshop on Asian Language Resources (ALR7), pages 24–31.

Bilal Naeem, Aymen Khan, Mirza Omer Beg, and Hasan Mujtaba. 2020a. A deep learning framework for clickbait detection on social area network using natural language cues. Journal of Computational Social Science, pages 1–13.

Saad Naeem, Majid Iqbal, Muhammad Saqib, Muhammad Saad, Muhammad Soban Raza, Zaid Ali, Naveed Akhtar, Mirza Omer Beg, Waseem Shahzad, and Muhammad Umair Arshad. 2020b. Subspace gaussian mixture model for continuous urdu speech recognition using kaldi. In 2020 14th International Conference on Open Source Systems and Technologies (ICOSST), pages 1–7. IEEE.

Dat Quoc Nguyen and Karin Verspoor. 2018. An improved neural network model for joint pos tagging and dependency parsing. In Proceedings of the CoNLL 2018 Shared Task: Multilingual Parsing from Raw Text to Universal Dependencies, pages 81–91.

Dong Nguyen and A Seza Doğruöž. 2013. Word level language identification in online multilingual communication. In Proceedings of the 2013 conference on empirical methods in natural language processing, pages 857–862.

Saira Qamar, Hasan Mujtaba, Hammad Majeed, and Mirza Omer Beg. Relationship identification between conversational agents using emotion analysis. Cognitive Computation, pages 1–15.

Hareem Sahar, Abdul A Bangash, and Mirza O Beg. 2019. Towards energy aware object-oriented development of android applications. Sustainable Computing: Informatics and Systems, 21:28–46.

Younes Samih, Suraj Maharjan, Mohammed Attia, Laura Kallmeyer, and Thamar Solorio. 2016. Multilingual code-switching identification via lstm recurrent neural networks. In Proceedings of the Second Workshop on Computational Approaches to Code Switching, pages 50–59.

Aditeshwar Seth and Mirza Beg. 2006. Achieving privacy and security in radio frequency identification. In Proceedings of the 2006 International Conference on Privacy, Security and Trust: Bridge the Gap Between PST Technologies and Business Services, pages 1–1.

Muhammad Tariq, Hammad Majeed, Mirza Omer Beg, Farrukh Aslam Khan, and Abdelouahid Derhab. 2019. Accurate detection of sitting posture activities in a secure iot based assisted living environment. Future Generation Computer Systems, 92:745–757.

Ahmed Uzair, Mirza O Beg, Hasan Mujtaba, and Hammad Majeed. 2019. Weec: Web energy efficient computing: A machine learning approach. Sustainable Computing: Informatics and Systems, 22:230–243.

Adeel Zafar, Hasan Mujtaba, Sohrab Ashiq, and Mirza Omer Beg. 2019a. A constructive approach for general video game level generation. In 2019 11th Computer Science and Electronic Engineering (CEEC), pages 102–107. IEEE.

Adeel Zafar, Hasan Mujtaba, Mirza Tauseef Baig, and Mirza Omer Beg. 2019b. Using patterns as objectives for general video game level generation. ICGA Journal, 41(2):66–77.

Adeel Zafar, Hasan Mujtaba, and Mirza Omer Beg. 2020. Search-based procedural content generation for gvg-lg. Applied Soft Computing, 86:105909.

Adeel Zafar, Hasan Mujtaba, Mirza Omer Beg, and Sajid Ali. 2018. Deceptive level generator.

Rabail Zahid, Muhammad Owais Idrees, Hasan Mujtaba, and Mirza Omer Beg. 2020. Roman urdu reviews dataset for aspect based opinion mining. In 2020 35th IEEE/ACM International Conference on Automated Software Engineering Workshops (ASEW), pages 138–143. IEEE.

Peng Zhou, Wei Shi, Jun Tian, Zhenyu Qi, Bingchen Li, Hongwei Hao, and Bo Xu. 2016. Attention-based bidirectional long short-term memory networks for relation classification. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 207–212.