# Augmented Deep Learning Model for Social Network Sentiment Analysis

**Suzan Hamed[*1], Mostafa Ezzat[2], Hesham Hefny[3]**

*Abstract:* Users of social media communicate their views, wants, socialise, and share their opinions as the number of users grows. Resources of high quality are required for social media sentiment analysis, but there aren't many of them available for languages other than English, especially Arabic. Both the amount of the corpus and the calibre of the annotations in the Arabic resources that are readily available are lacking. In this study, we offer a Facebook-sourced Arabic sentiment analysis corpus with 60K comments that have been manually marked as a gold standard and classified as positive and negative. In order to annotate the corpus, we used self-training and remote supervision techniques. in this paper we propose a deep learning approach that allows companies and organizations to evaluate users' opinions on the quality of their services, by analysing their opinions on Facebook. We display three deep Learning models Convolutional Neural (CNN), Recurrent Convolutional (RCNN), Long Term Memory (LSTM) for Arabic sentiment analysis with the assistance of word embedding. The model accuracy was measured, and we got average accuracy of 82.1 % which was better than both CNN and RCNN. Also, applying increasing that data to the body increments LSTM accuracy by 8.7 %.

*Keywords: Deep learning, CNN, LSTM, RCNN, Sentiment analysis, social media analysis*

## 1. Introduction

Nowadays, there's a parcel of online conclusions. This information is imperative for clients since it helps them to form decisions about buying an item, voting in a political race, and choosing a travel goal, among other subjects. This information is additionally vital for organizations since it helps them to know the common conclusion almost their products, the deals estimate, and the client fulfilment in real time. Based on this data, companies can identify opportunities for making strides the quality of their items or services.

Arabic is positioned 4th within the world, with 237 million Web clients [1]. Hence, it is critical to create opinion analysis instruments for this language. Arabic is the foremost dynamic part of the community of Semitic languages in terms of speakers, being utilized in North Africa, the Centre East, and the Horn of Africa. It has three classes, modern standard Arabic (MSA), tongue Arabic (DA), and classical Arabic (CA) [2]. Sentiment analysis has been characterized by many creators. However, the definition most utilized inside the investigate community is the proposed by [3],who characterized it as takes after: "Sentiment examination is the field of consider that investigates people's suppositions, estimations, evaluations, assessments, attitudes, and sentiments towards substances such as things, administrations, organizations, individuals, issues, events, subjects, and their attributes."

Most of the deep-learning-based approaches for presumption analysis are based on the English tongue.

Hence, we propose a significant learning-based approach for conclusion examination of Facebook comments in Arabic.

Essentially, the work of [4] which collected 1800 number of tweets interior the Jordanian Arabic tongue and compared the execution of SVM and NB utilizing n-grams methodologies and a handful of contrasting acknowledgment methods. As well, the work of [5] has moreover compared and executed SVM with the Kuwaiti Arabic choice tree related to the National Get together. Comparable work endorsed in [6] to dissect estimation is related to a set of 1,103 Saudi tweets.

The most objective of this investigate is to provide an explained gather of 60.000 social media comments composed in colloquial Arabic in arrange to survey the opinions of individuals within the governorates of Giza and Cairo. Furthermore, this paper employments the stack to build three profound learning approaches: Convolutional Neural Arrange (CNN) [7], Long Term Memory (LSTM) [8], and Neural Network Recurrent Convolutional Convolution (RCNN) [9]. An appraisal is additionally advertised by comparing the three models utilizing the pre-trained word inserting procedure known as CBOW. In expansion, that distribution gives a few information increases encounters.

The leftover portion of the paper is laid out as takes after: Caste number two, in which the proposed combination is appeared.

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Segment 3 talks about the profound learning models that have been proposed. Segment 4 outlines the exploratory discoveries and surveys the proposed profound learning models for the proposed gather. Segment 5 examines related work within the same point, especially that including profound learning approaches. At long last, area (6) brings the paper to a nearby.

## 2. Arabic Sentiment Analysis

On the web, there are many diverse lingos. According to [10] Arabic is the fourth most prevalent dialect on the web, with 237 million clients. As a result, it is basic to create possible examination gadgets for this tongue. Over terms of speakers, Arabic is the foremost energetic of the Semitic lingos, with speakers in North Africa, the Centre East, and the Horn of Africa. It is partitioned into three categories: advanced standard Arabic (MSA), lingo Arabic (DA), and classical Arabic (CA) [11].

## 3. System architecture

In this section, we explain the main components of our system. First, the comments undergo a pre-processing and cleaning phase to remove unwanted icons and icons. Then the comments are ready to be ready for the training phase. We train three deep learning models, the Convolutional Neural model (CNN), the Long-Term Memory model (LSTM), and the Recurrent Convolutional model (RCNN). After training both models with different hyperparameters, we choose the best models with the highest score in F1 and after comparison we use the Bi-LSTM data augmentation application. We use the ensemble model to predict the final sentiment of incoming comments.

The comments collected extend from November 24, 2019 to June 18, 2020. At that starting organize, a gather of 33250189 metal comments were collected. Which bunch contains comments composed in Standard Arabic and another inside the Egyptian tongue. Though inside the minute organize of building that bunch, it is considered floundering, and the securing of those comments. At that organize, we perform a manual determination of those communes, to decide whether those communes are composed inside the classical shape or inside the Egyptian lingo.

The first objective of this approach is to recognize fundamental data around things and organizations that grants companies and organizations to make strides them. In this way, our approach requires a corpus related to things and organizations. In appear hate toward of the truth that a few corpora have been given interior the composing, there's a require of corpora for Arabic comments. In this sense, we have gotten a corpus from Facebook in Arabic. The arrange for collecting this corpus is depicted underneath.

(1) comments were collected by utilizing Facebook API. To induce vital comments, a set of watchwords related to imaginative things were characterized.

(2) Replicated comments, re-comments, comments in other dialects, and comments that contain because it was URLs were emptied.

(3) We gotten a include up to of 50000 positive tweets and 43000 negative tweets.

(4) At long final, we chosen because it was 30000 positive comments and 30000 negative comments, which were physically analyzed to urge those noteworthy to our think about.

### 3.1. Feature extraction

**Table 1.** comments corpus statistics

| Total number of comments | Number of positive comments | Number of negative comments | Number of words | Max comments token | Number of taken | Average tokens per comment |
|---|---|---|---|---|---|---|
| 60000 | 30000 | 30000 | 359818 | 90 | 1953869 | 17 |

Our suggested framework's overall architecture is divided into three phases: data preparation, extraction of features, and classification. The political Arabic comments are collected, preprocessed, and labelled during the data preparation phase. The feature vectors were constructed using word embedding with CNN, RCNN, and LSTM in the feature extraction phase. The SoftMax function was used in the classification phase to detect the opinions of the political Arabic comments.

**Layer for embedding.**

The entry is a comment (sentence)S, which is a series of words $w_1$, $w_2$,.....$w_d$ each selected from a limited vocabulary V. A lookup table converts each word into a low-dimensional vector: $x_i = E_w(w_i)$,where $W \in R^{d_w} \times |V|$ is the word embedding matrix, and $d_w$ is both words embedding dimension. As a consequence, the initial comment sentence is encoded as a matrix, with each column representing a different word embedding.

**Convolutional layer.**

We obtain specific n-gram attributes from the embedding matrix using a set of m filters in this layer. Using a sliding window of size w, and the filter $F_l$ $(1 \leq l \leq m)$, the convolutional feature output $z_i^l$ can be created as follows:

$z_i^l = f(x_{i;i+w-1} \times w^l + b^l)$ (1)

Where $x_{i;i+w-1}$ signifies the word vectors, $W \in R^{w \times d}$ is the weight matrix, b is a bias, and denotes a convolution operation. The filter $F_l$ produces the output $z^l \in R^d$, where $z_i^l$ is the i-th element of $z^l$. The activation function was Rectified Linear Units.

**Max-Pooling layer.**

To extract the most relevant features, we use the max-pooling procedure on each filter. Each $z^l$ row of yields the maximum value, which is used to build the next particles. A dropout approach was used in CNN to avoid the overfitting problem.

**Bi-LSTM layer.**

One-way traffic The Long Short-Term Memory (LSTM) is insufficient, and it may be unable to leverage the contextual

information provided by succeeding words. By processing the sequence in both forward and backward orientations, the Bi-LSTM was able to leverage both recent and future contexts.

## 4. Literature review

In this range he summarizes the work related to supposition examination especially Related to the brief Arabic substance by utilizing machine learning. There are various explore endeavors in significant learning that center on English estimation examination. Various works have utilized Long Short-Term Memory (LSTM) to appear sentiments. Such as Work in [12] associated the Long Short-Term Memory (LSTM) to a set of 3,200 tweets inside the English tongue that contained emojis. [18] used an antagonistic profound averaging organise (ADAN) show [19] to transfer knowledge learnt from labelled data on a resource-rich source dialect to a low-resource dialect with unlabeled data.

[20] used a CNN to connect three datasets: one in English, one in German, and one in Arabic. [21] conducted a thorough comparison analysis of several highlight making designs for content sort classification using machine learning and gathering methodologies. The potential of such tactics for distinguishing estimation looked to be encouraged as a result of this. [12] linked CNN-LSTM and CNN-BiLSTM models that included Word2vec and GloVe embeddings to two datasets: the Stanford Assumption Treebank (SST) [22] and a private Chinese tourism survey dataset. They adopted a unique cushioning approach that appeared to improve execution when compared to zero paddings. CNN-LSTM had the best accuracy, with 50.7 percent (SST) and 95.0 percent (Chinese). [20] utilized a demonstrate based on CNN whereas [23] utilized LSTM. [24] and [25] combined CNN with LSTM. Our two proposed approaches are based on CNN and CNN through BiGRU, individually (see following segment).

The challenge which faces opinion investigation is the need of labeled information in NLP. This audit paper portrays the most recent considers which concern with fulfillment profound learning models to sentiment analysis as profound neural systems, convolutional neural networks, and others to fathom different problems [26].

[27] applied convolutional neural networks (CNNs) to a few dialect errands, counting estimation investigation, using word vectors. This appeared to be the approach's potential. The Stanford Opinion Treebank (SST) dataset [22] was used to link the method to sentiment classification.in [29] It has been divided into the following categories: Positive, Extremely Positive, Negative, Extremely Negative, and Indifferent. They compared the LSTM's execution on both items, and those results nearly revealed the highest hoisting precision inside the first bunch, with a precision of 70%.

## 5. Proposed approach

The focus of this research is to construct framework recognize political Arabic Facebook sentiments. This is by first putting in place a deep learning model for Comparing different machine learning techniques with Arabic text the proposed strategy A typical strategy for data in NLP modeling is a process of converting a string of text into a feature vector.

Long Short-Term Memory (LSTM) and convolutional neural (CNN), Recurrent Convolutional (RCNN) are examples of neural network methods. In many NLP tasks, convolutional neural CNN has been utilized for syntactic and semantic representations of text, and it has achieved better classification performance than traditional NLP approaches. The input size of a CNN algorithm is usually larger than the filter size. As a result, the outcome interactions with a small portion of the input, highlighting the n-local gram's lexical relationships. Long Short-Term Memory (LSTM) can retain long-sequence dependencies and is effective for sequence modelling, but it may fail to retrieve the local n-gram environment.

Our suggested framework's overall architecture is divided into three phases: data preparation, extraction of features, and classification. The political Arabic comments are collected, preprocessed, and labelled during the data preparation phase. The feature vectors were constructed using word embedding with CNN, RCNN, and LSTM in the feature extraction phase. The SoftMax function was used in the classification phase to detect the opinions of the political Arabic comments.

Three models of significant learning are proposed on a proposed set of Facebook comment classification that's subsequently entered into presumption examination records, whether positive or negative. In common, the paper proposes CNN, LSTM, and RCNN significant learning models. They are among the common shapes utilized inside the significant composing for learning classification assignments, particularly in estimation examination [ [24]- [27]- [17], [30]] (CNN), may be a specialized sort of neural organize accumulated from the human visual cortex and utilized in computer vision since it to boot a lively neural orchestrate in which data is transmitted since it was interior the forward course [31].

A CNN may more regularly than not incorporate of a few convolutional layers that act as an extractor for different adjoining highlights of the information, in any case of where these neighborhood highlights are. As these properties are considered fitting for classification errands in common tongue dealing with. The objective here of classification is to memorize a specific course of action of words as incredible pointers of them in any case of their position inside the sentence. For this reason, convolutional neural (CNN) has been utilized viably in various texts' classification errands. [27] associated convolutional neural systems (CNNs), working over word vectors, to a couple of dialects preparing errands, checking estimation examination. this appeared the potential of such an approach. [27] gotten a frame of CNN where the thick layer is supplanted with a long short-term memory (LSTM) layer. the abdicate of the convolution is energized to the LSTM layer in this way combining the benefits of each handle. the technique was associated to estimation classification with the Stanford Estimation Treebank (SST) dataset [22]. Furthermore, RCNN is defined as a system that incorporates some properties of both convolutional neural (CNN) and Long Short-Term Memory (LSTM), i.e., convolutional neural (CNN) is used as a powerful highlight extractor, and the LSTM layer is used to attach the painstaking neural organising plan to those highlights for extraction. As shown in Figure 1 there are three models.

Each illustration has an input layer first, followed by organise plan layers. By using the word2vec embedding [36], the input layer may be an uninspiring vector representation of those words.

In common, word inserting is one of the strategies of profound

able learning and tongue modeling, which in turn critically changes the words fittingly into a vector of genuine numbers. Too, this conspire incorporates vector input for long gauges, since they are inside the vector design of a single hot cipher, in a vector with least estimates. In common, there are two shapes in Word2vec, which are known as: Tireless Pack of Words (CBOW) too known as skip-gram [36]. In CBOW, it predicts the target word from the setting words, and skip gram predicts the setting
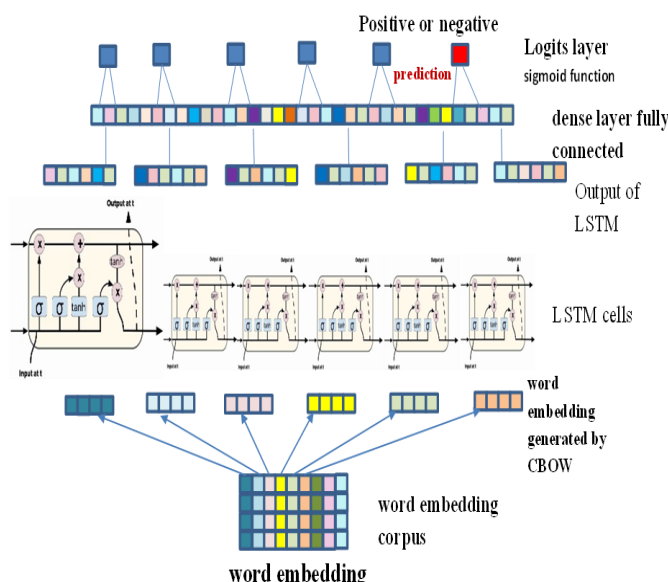


**Fig. 1.** General architecture of the proposed models

words from that target word. In those proposed models for critical learning, we utilize vectors for those words organized utilizing Word2vec. Particularly the CBOW, where interior the CBOW outline pre-trained words are utilized, which is known as Aravec [37]. Those word inserting sentences that have been made as an input join are at that point nourished to each framework through the word inserting organize. Layers are portrayed for each organize. This outline was organized on a set of 80,000,000 Arabic comments on Facebook A incorporate up to of 1,982,125 words. It is at that point made based on a pre-trained CBOW illustrate. Word Thought Sentences made by the organize are at that point energized into a word embed cross section as an input incorporate for each. Underneath we depict the layers of each

### 5.1. convolutional neural model (CNN)

The evaluate is shown inside the convolutional neural (CNN) appears structure by applying a word embed layer, and the embedded sentence is enabled to the CNN appears layers. The fundamental layer of CNN might be a convolution layer with 16 different channels (each with 2 porousness) to remove the highlights of the strings. These convolutions wrap the input and give integrated maps (of variable length). The lipid layer, on the other hand, is the third layer, which integrates all of the highlights into a consistent arrangement. A thick (totally related) sigmoid layer could be the final layer [38]. It serves as a sanctioning function. This layer generates the organize's abdicate, which changes depending on whether the input sentence is negative or positive.

### 5.2. Long Short-Term Memory **model (LSTM)**

In Long Short-Term Memory (LSTM) , it comprises of a memory cell as well as an input entryway moreover a surrender entryway and a neglecting entryway. As the memory cell is careful for reviewing those values over time, while the other entryways are careful for controlling the stream of that entirety of information into and out of the cell. LSTM layers are showed up in Figure 2. These embedded words are as well entered into LSTM cells after the embedded word layer has been associated to them. The LSTM cells are as well arranged on the embedded words, so they make a couple of prescient words for them. These estimate words are emphatically and unequivocally related with a thick layer [38].
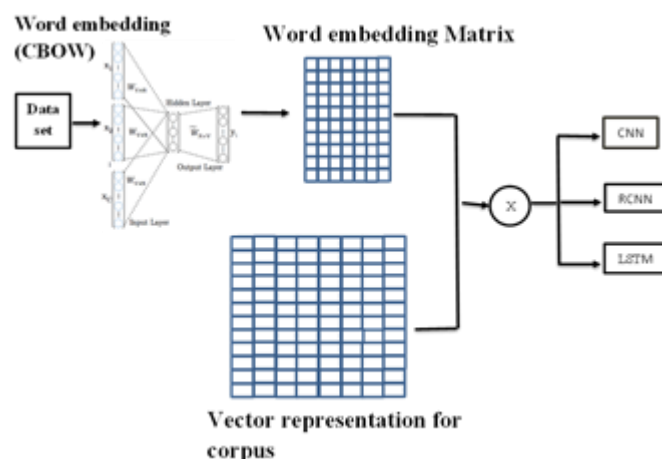


**Fig. 2.** Layers of LSTM

### 5.3. Recurrent Convolutional model (RCNN)

Format and save your graphics using a suitable graphics processing program that will allow you to create the images as PostScript (PS), Encapsulated PostScript (.EPS), Tagged Image File Format (.TIFF), Portable Document Format (.PDF), or Portable Network Graphics (.PNG) sizes them, and adjusts the resolution settings. If you created your source files in one of the following programs you will be able to submit the graphics without converting to a PS, EPS, TIFF, PDF, or PNG file: Microsoft Word, Microsoft PowerPoint, or Microsoft Excel. Though it is not required, it is strongly recommended that these files be saved in PDF format rather than DOC, XLS, or PPT. Doing so will protect your figures from common font and arrow stroke issues that occur when working on the files across multiple platforms. When submitting your final paper, your graphics should all be submitted individually in one of these formats along with the manuscript.

## 6. Performance parameter for evaluation

A perplexity framework may be a sort of lattice which is able be utilized to distinguish the rightness of classifiers. In parallel classification an issue is that each event of the test data is doled out to a component It encompasses a put to bunch P, N of the classification of negative and positive categories. To recognize between predicate and genuine classes the names Y, N are utilized. Given a illustrate and a case, there are Four conceivable yields. Whereas in case an event is at first positive and it is classified as positive, at that point it is recorded as honest to

goodness positive (TP), but in case it is classified as negative, at that point it is recorded as off-base negative (FN).From another heading, in case the case is at first negative and is classified as negative, it is at that point recorded as honest to goodness negative (TN), but on the off chance that it is categorized as positive, this condition is tallied as unfaithful positive (FP).

This perplexity is due to the appear and a set of test set cases Where the arrange can be made from the life structures of cases. Suitably, the perplexity of the assessment organizes of significant learning models [8]. The first common appraisal estimations are accuracy and review the precision is F1 and is chosen utilizing the taking after equations:

The first common appraisal estimations are accuracy and review the precision is F1 and is chosen utilizing the taking after equations:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1score} = \frac{2 \times Precision \times Recall}{Precision+Recall}$$

## 7. Experimental results and discussion

. This segment appears the test comes about of applying CNN, LSTM and RCNN model on the proposed corpus. We train and test each model utilizing different information parts, particularly (80%, 20%), (70%, 30%) and (60%, 40%), considering that 10% is taken as approval sets for the hyper-parameter tuning. Also, we perform fvefold cross-validation on each information split to urge more strong execution by averaging 5 different runs per each information part. Since positive and negative classes are similarly conveyed within the corpus, the accuracy is considered a palatable execution metric to assess the models. Be that as it may, we take moreover into consideration exactness, review and f-score as execution measurements in arrange to draw a clear elucidation of the comes about. Moreover, other than the assessment of the models on the corpus, we additionally apply the information enlargement strategy on a few experiments [39]. The point of this strategy is to doubly increment the full degree of the corpus in organize to test the primary really effect of the expanded information on the execution of the three models. By and clearing, there are distinctive strategies that can be gotten a handle on in data increment like commotion implantation, words moving forward and lexical substitution which changes a word by its synonym utilizing a particular thesaurus [40]. Table 3 also shows the CNN outline and its optimal lines of action in addition to the parameters. The frequency of the course of activity used in this setup is 60, which corresponds to the size of the most remarkable comment, implying that the most noteworthy Comment is 60 words long. Furthermore, 32 channels were used, each of which could move in 16 different sizes and be grouped for the region. The survey of lexicon entering the framework, or the number of words entered each time, was set to 10,000 words. In common, an arrangement of tests was performed in a deliberate strategy within the middle of the introduction period to enact the drive set of common additionally distinctive hyperparameters.

**Table 2.** Hyper-parameters values for LSTM, CNN and RCNN models

| Models | Batch size | Dropout rate | Learning rate ($\alpha$) | Numbers of epochs |
|--------|-----------|--------------|-------------|-------------------|
| RCNN | 200 | 0.7 | 0.001 | 100 |
| LSTM | 1000 | 0.5 | 0.001 | 100 |
| CNN | 200 | 0.7 | 0.001 | 100 |

**Table 3.** configuration of Convolutional Neural (CNN) parameters

| Sequence length | Batch size |
|-----------------|-----------|
| RCNN | 200 |
| LSTM | 1000 |
| CNN | 200 |

**Table 4.** configuration of Long Short-Term Memory (LSTM) parameters

| LSTM size | LSTM Layer |
|-----------|-----------|
| 256 | 1 |

**Table 5.** configuration of Recurrent Convolutional (RCNN) parameters

| | |
|-----------------|-------|
| Sequence length | 60 |
| Number of filters | 32 |
| Filter size | 16 |
| Number of LSTM layer | 128 |
| LSTM units | 1 |
| Vocab size | 10000 |

Table 2 shows the introductory settings of hyperparameters required to run these three models. In expansion, by averaging 5 dissimilar runs for each data dissemination, we execute a fivefold cross-check on each of these information mappings with the objective of empowering the foremost strong and prevailing execution. Moreover, given the unambiguous division between the negative and positive categories, the precision scale score will be sufficient for rating these models. Be that since it may, we as well ought to take underneath thought the degree of precision as well as the review and score f as execution measures in organize to draw a clear coherent elucidation of the comes around. Other than evaluating these models on the body, we have as well related a strategy called information increase in numerous tests.

As well, Table 4 appears up what are the finest LSTM courses of activity. This config applies since it was one LSTM layer which may contain 256 LSTM cells. In expansion, Table 5 appears up the RCNN illustrate with its best courses of action. This outline may be a blend between the two past models, which have the same values for the same courses of activity. As well, Table 6 summarizes a handful of the entire comes around of the CNN appear tests. Those comes nearly showed up that the preeminent imperative exactness rate was gotten, which was 78.80%, 77.48%, and 79.99 % interior the information allocated as 80/20 ,70/30 and 60/40, only. While, the in common normal. for the execution of the LSTM show up for the respect of the f-degree was 76.96%.

In Table 7, the exploratory comes around are completely summarized for LSTM. Those comes roughly appeared up that

the preeminent lifted ordinary precision was gotten for each information disengaged as takes after: 82.56%, 82.4% and 82.35%, in isolating that information, independently for (80/20), (70/30) and (60/40). In expansion, the commonplace for the foremost portion respect score is f 82.1%. Other than, the preeminent raised commonplace f-score satisfied for each information parcel is 81.49%, 81.43% and 80.84% interior the information parcel (80/20), (70/30) and (60/40), solely. The in common ordinary respect of f-score is 81.25%. Extra tests are run to see how well the LSTM performs after the information has been expanded. Table 9 depicts the LSTM with expansion in its entirety.

The average precision has increased by 7.45 to 8.86 percent in some information areas, with the first raised average precision obtaining 88.71 percent, 87.76 percent, and 87.68 percent, respectively, inside the information parcels (80/20), (60/40), and (70/30). In LSTM with amplified information, averaging the accuracy values for each information parcel yields a common

ordinary precision score of 88.05 percent. The comes around appear up that the common commonplace accuracy is amplified by 8.3% compared to the comes around of LSTM a couple of times as of late applying information increase. In expansion, the common commonplace f-score respect satisfied is 87.24% with the increment of 7.37% than the common f-score of the LSTM a couple of times as of late applying information development. The test comes around were appeared and completely depicted for RCNN in Table 8. These comes nearly appeared up that the first lifted normal exactness was gotten in each of these information divisions is 79.84%, 77.28% and 81.8% interior the information division as takes after are freely (80/20), (70/30) and (60/40). To initiate the for the most part exactness of the RCNN outline, the conventional "accuracy values" interior the RCNN show up are calculated for each information division. While, the by and large precision of the RCNN outline was 79.26%. Other than, the first raised merciless f-score gotten for each information parcel was 77.96%, 77.82% and 77.81% in (80/20), (70/30) and (60/40) independently.

#### Table 6. AVG performance for various data split with CNN model

| model | Split | Average accuracy (%) | Average recall (%) | Average precision (%) | Average f-score (%) |
|---|---|---|---|---|---|
| CNN | (80 % , 20 %) | 73.65 | 73.85 | 75.21 | 72.43 |
| | (70 % , 30 %) | **78.8** | 77.54 | **79.99** | 78 |
| | (60 % , 40%) | 78.42 | **77.48** | 79.84 | 77.87 |
| Total AVG | | 76.96 | 76.29 | 78.34 | 76.1 |

#### Table 7. configuration of RCNN parameters

| model | Split | Average accuracy (%) | Average recall (%) | Average precision (%) | Average f-score (%) |
|---|---|---|---|---|---|
| LSTM | (80 % , 20 %) | 82.44 | **82.4** | 82.84 | **82.35** |
| | (70 % , 30 %) | **82.56** | 81.74 | **83.61** | 82.13 |
| | (60 % , 40%) | 81.31 | 81.03 | 82.96 | 81.63 |
| Total AVG | | 82. 1 | 81.72 | 83.13 | 82.03 |

#### Table 8. AVG performance measures for various data divisions with RCNN model

| model | Split | Average accuracy (%) | Average recall (%) | Average precision (%) | Average f-score (%) |
|---|---|---|---|---|---|
| RCNN | (80 %, 20 %) | **79.84** | 77.46 | **81.8** | 78.62 |
| | (70 %, 30 %) | 79.23 | **77.28** | 80.45 | **78.65** |
| | (60 %, 40%) | 78.72 | 76.48 | 79.67 | 77.97 |
| Total AVG | | 79.26 | 77.07 | 80.64 | 78.41 |

#### Table 9. AVG performance measures for various data divisions with LSTM + Augmentation model

| model | Split | Average accuracy (%) | Average recall (%) | Average precision (%) | Average f-score (%) |
|---|---|---|---|---|---|
| LSTM | (80 %, 20 %) | **89.83** | 89.51 | | **89.32** | **89.32** |
| | (70 %, 30 %) | 88.26 | **89.74** | | 87.56 | 86.32 |
| | (60 %, 40%) | 88.64 | 88.9 | | 87.93 | 88.46 |
| Total AVG | | 88.91 | 89.38 | | 88.27 | 88.03 |

#### Table 10. Comparison of the AVG performance of CNN, LSTM and RCNN models

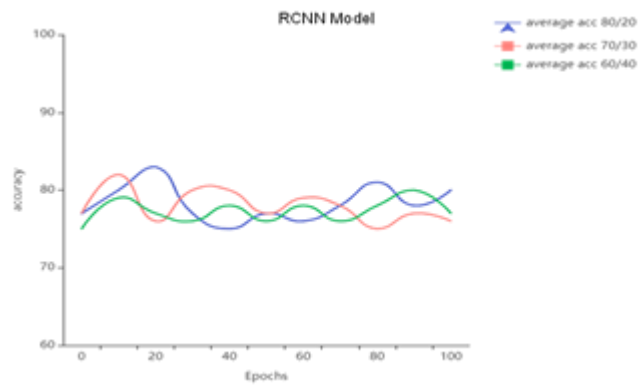| model | Average accuracy (%) | Average recall (%) | Average precision (%) | Average f-score (%) |
|---|---|---|---|---|
| CNN | 79.69 | 76.29 | 78.34 | 76.1 |
| RCNN | 79.26 | 77.07 | 80.64 | 78.41 |
| LSTM | 82.1 | 81.72 | 83.13 | 82.03 |
| LSTM +Aug | **88.91** | **89.38** | **88.27** | **88.03** |

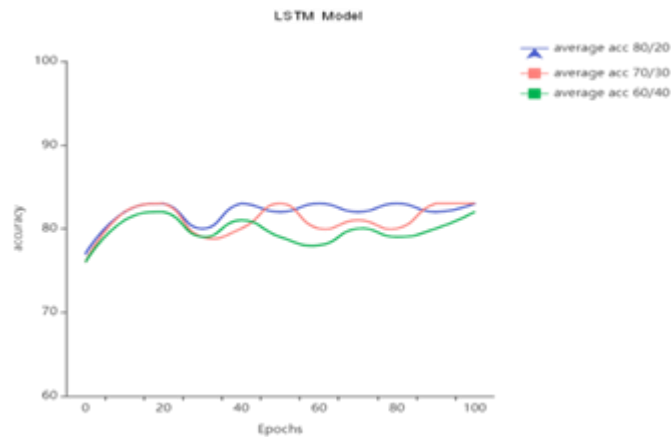Fig. 3.  AVG training accuracy per 100 epochs for various data split of the RCNN model



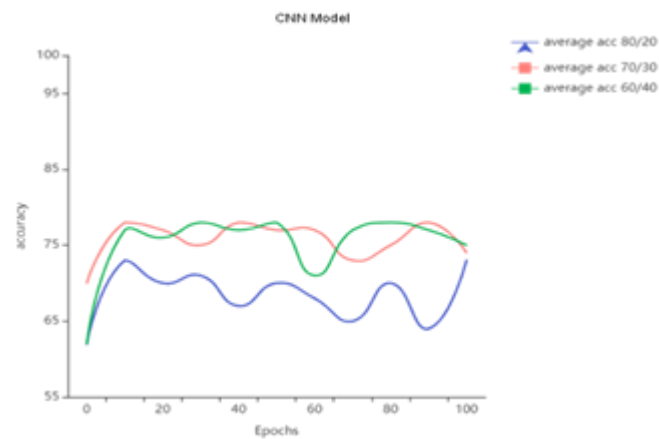Fig. 4.  AVG training accuracy per 100 epochs for various data split of the LSTM model



Fig. 5.  AVG training accuracy per 100 epochs for various data split of the CNN model
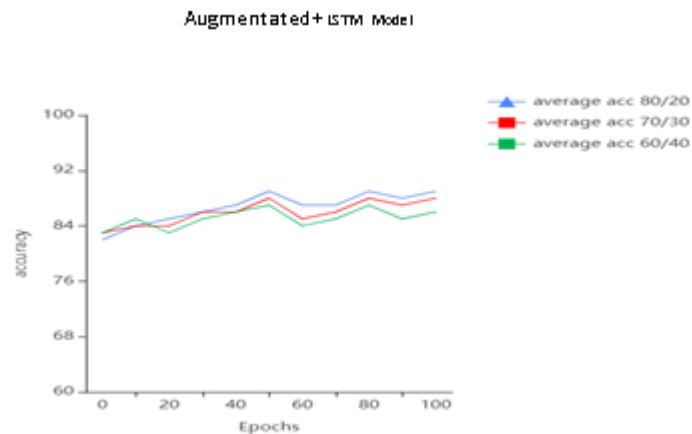


Fig. 6.  AVG training accuracy per 100 epochs for various data split of the Augmented + LSTM model

In 7.1, the comparison and conversation of what was appeared, as Figures (3,4,5,6) appears up the comparison between the arranging accuracy for each 100 periods in organize to restrict the assorted information for the varying models. In common, interior the arranging arranges, which is insides noteworthy learning, utilizing those scattered checked on degrees, the accuracy is measured for each Boost since it tends to swing up and down. It is common that a gloomy increment interior the degree of precision isn't gotten, insides each of which is what is known as clumps. The normal procedures of managing with exactness are by calculating the degree of conventional exactness each time for all clumps. Interior the tests, not since it was all clusters found the middle regard of, but 5 unmistakable disseminations were moreover run for each information division. Like in each age on commonplace we run 5 different scatterings to restrict the information as takes after (80, 20) where the age talks to the complete conventional diffusing for all sizes of divisions of the information. As these comes almost reveal that the normal planning precision interior the show up CNN is one of the primary precarious models for information division in comparison to other models.

As well, the standard deviation of the conventional accuracy of the divisions of these data is 3.10 compared to 0.35 and 0.57 in both LSTM and RCNN models, openly. This appears up that the commonplace accuracy of both LSTM and RCNN is steadier and more grounded. As a run the show as often as possible in show up abhor toward of the truth that RCNN combines the characteristics of both LSTM and CNN, as well as its standard deviation between data divisions, since the ordinary precision is less than that of the LSTM, as the standard exactness comes about of the LSTM show up have beated the RCNN show up. More frequently than not due to the separate interior the input Ordinarily regularly for each layer of LSTM in both models. It is getting a layer from the LSTM as an input and its internal parts the RCNN That's, it works on the run of those expelled highlights since it was on the LSTM layer interior the RCNN. Other than, it can utilize the LSTM layer on all the sentence words interior the LSTM show up that come coordinate from the insert since it jams the arrange of those words inside the sentence, in separate to RCNN, which is restricted to specific removed highlights.

CNN, LSTM, and RCNN are the three models. Regardless, the results show that the LSTM outperforms both the CNN and the RCNN in terms of precision and outcome. In addition, the degree to which the organise is considered in LSTM is noticeable, as well as in RNNs that rely on the position of each word, as well as within sentences. In this way, in both CNN and RCNN, the orchestration of those words is absolutely irrelevant.

In this way, its principal objective is the characteristics of the given words. In addition, the put of the word isn't critical inside the sentence. Hence, these two models CNN and RCNN may require more such data from our Arabic bunch in organize to advance these comes about.

### 7.1. Comparison and discussion

We examine the degree of planned exactness for each 100 ages in Figures (3,4,5,6) and split this unambiguous data into a few of the models that were used. The degree of correctness of each clump was measured in the middle of the planning handle, inside the critical learning by utilising the extents of the subjective slant,

because it tends to waver up and down. We don't usually see that bleak increase in the degree of exactness within each clump. The standard approaches for controlling the degree of exactness are to determine the average for accuracy on all clusters in each time separately. In these tests, we not because it was found the center esteem of all clumps but besides ran 5 unmistakable scatterings of that data and portion it up. Case, the rosy line plotted for CNN in Figures 6 talks to the ordinary (80, 20) data division precision for each period. Since in each age, we ordinary 5 assorted bunch sizes of data to be run (80, 20) and the age of each dispersal talks to the unfeeling of all bunch sizes of the data.

Furthermore, these results almost show the average level of planning precision within the CNN appear, since CNN is more susceptible to data division than other models. Though the terrible precision across data portions has a standard deviation of 3.10, compared to 0.35, 0.57, and 0.31 in LSTM, LSTM with extending, and RCNN, respectively. The typical exactness of LSTM and RCNN looks to be the dominant consistent and initially strong.

In spite of the fact that RCNN combines the qualities of LSTM and CNN, and its standard deviation of brutal precision across data divisions is smaller than LSTM, the ordinary precision that LSTM produces is more prominent in RCNN. Normally, due to the refining of each LSTM layer's input in both models. The solid highlights taken from the previous layer impregnated by the CNN in any scenario of the position of the words inside the input text are fed into the LSTM layer inside the RCNN as input.

To put it another way, the LSTM layer in RCNN works on the extricated highlights' position. Instead of confining the restricted deleted highlights like in RCNN, the LSTM layer within the LSTM appear livelihoods all the sentence words coming from the embed specifically and keeps up the pattern of the sentence words. Table 9 displays the typical by and expansive comes almost for CNN, LSTM, and RCNN shape estimations. In terms of accuracy and f-score, it appears that LSTM has the upper hand over CNN and RCNN. In addition, LSTM with expanded data completes the most crucial precision and most raised f-score, respectively, with values of 88.05 percent and 87.24 percent.

It got to be popular that applying the data broadening handle to both CNN and RCNN models does not have any vital affect, since the comes around gotten in both cases are undefined. Ordinarily due to the reality that the thought of sporadic modifying is grasped as an increased strategy, in which the organize of words inside the bunch is changed. This arrange is significantly considered with LSTM since it is an RNN also depends on the position of each word inside the sentences. In any case, in CNN and RCNN word orchestrate does not matter. Instep, the qualities of certain words are the foremost destinations. It doesn't matter where the word is inside the sentence. So, these two models, CNN and RCNN, require more honest to goodness data from our Arabic bunch to advance the comes around.

## 8. Conclusion

As of late, profound learning strategies have appeared a extraordinary affect and effective strategies in a wide extend of applications like machine interpretation, discourse acknowledgment, computer vision and NLP. Of late, applying profound learning procedures to sentiment investigation has

gotten to be progressively prevalent and outperformed standard machine learning calculations when bigger information is accessible. Hence, a extraordinary bargain of inquiries about applied profound learning strategies on assumption investigation on several talked dialects. The Arabic dialect is one of the most broadly utilized dialects within the world and is utilized broadly on social media with different shapes and tongues

Be that as it may, one confinement to apply profound learning procedures on Arabic opinion examination is the accessibility of reasonable large corpora. In this way, this paper presented labeled corpus of 60k Arabic comments talking about the opinions of people in Giza and Cairo governorates. In this paper, I collected 60 thousand Arabic comments examining people's suppositions with respect to the work of both governorates Giza and Cairo this comment was collected by API. at that point information isolated separately for (80/20) , (70/30) and (60/40). In expansion, the paper has connected three profound learning methods to the proposed bunch. In specific, the paper has tested a execution of the gather on CNN, LSTM, and RCNN. With the assistance of word implanting innovation as an input layer for the three models, LSTM with 82.1% exactness outflanked CNN with 76.96% exactness and RCNN with 79.26% exactness. Whereas applying this information increase strategy to the body, LSTM appeared an extra great enhancement with an exactness of 88.91%. This can be since this increase strategy includes an exceptionally enormous effect on body estimate as well as on the execution of those models for profound learning, and other diverse sorts of increase methods can too be joined as a future work.

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