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Original Article

An Integrated Cycle GAN and PEGASUS to Generate Synthetic Data for Detection of Fake News

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Abstract - *The proposed research to increase the size of the dataset with images, the regular image manipulation, which involves an image translation process using different graphical operations, makes the entire workflow design expensive. This process also involves designing complicated structures, which takes a lot of time to build the complete architecture. This image translation process has a major drawback, which involves controlled modification of the images. So, the proposed system implemented an Enhanced Cycle GAN, which does not perform any pairing activity between the images in the dataset. Since the detection of fake news involves both images and texts, the proposed research extracts the text using an ensemble mechanism in which the text summarizer is constructed using the pre-trained model known as "PEGASUS" combined LSTM to perform abstractive text summarization. After framing the summarization based on the context, the system is evaluated to prove its efficiency using ROUGE-N metrics.*

Keywords - *PEGASUS, pre-trained model, ROGUE-N, Abstractive Summarization, Cycle GAN, Recurrent NN models, Gradient Recurrent, Unit (GRU), Optimizer.*

1. Introduction

Generative Adversarial Neural Networks are famous for creating similar images containing synthetic data relevant to the original data. GANs exist in 6 popular forms, as shown in figure 1.

There are various real-time applications of GAN like predicting the next frame while capturing the video in live stream scenario, resolution of the images can be improved, known as "Progressive GAN", and they can efficiently convert the text values into images. They can also perform translation of one image to other images, which is known as "Cycle GAN"[16]. This neural network learns the probability of the observations it tries to learn during the training phase. New images are created that are nearer to computed probability values.

Working with textual data involves NLP, which performs summarization operation using either abstractive or extractive mechanisms. The major goal of summarization is to provide the user with the overall concept of the information without changing its meaning in a short note highlights. An extractive mechanism generates the sub forms based on their verbal notations. In contrast, an abstractive mechanism analyzes the text, understands the context, and makes it shorter based only on important information. In general, performing abstractive summarization uses the concept of encoder-decoder [12], in which the attention layer is added as an intermediate layer to produce a sequence of information as a feature vector by passing through GRU layers at every possible hidden layer. The Encoder-Attention-Decoder (EDA) architecture is illustrated in figure 2.

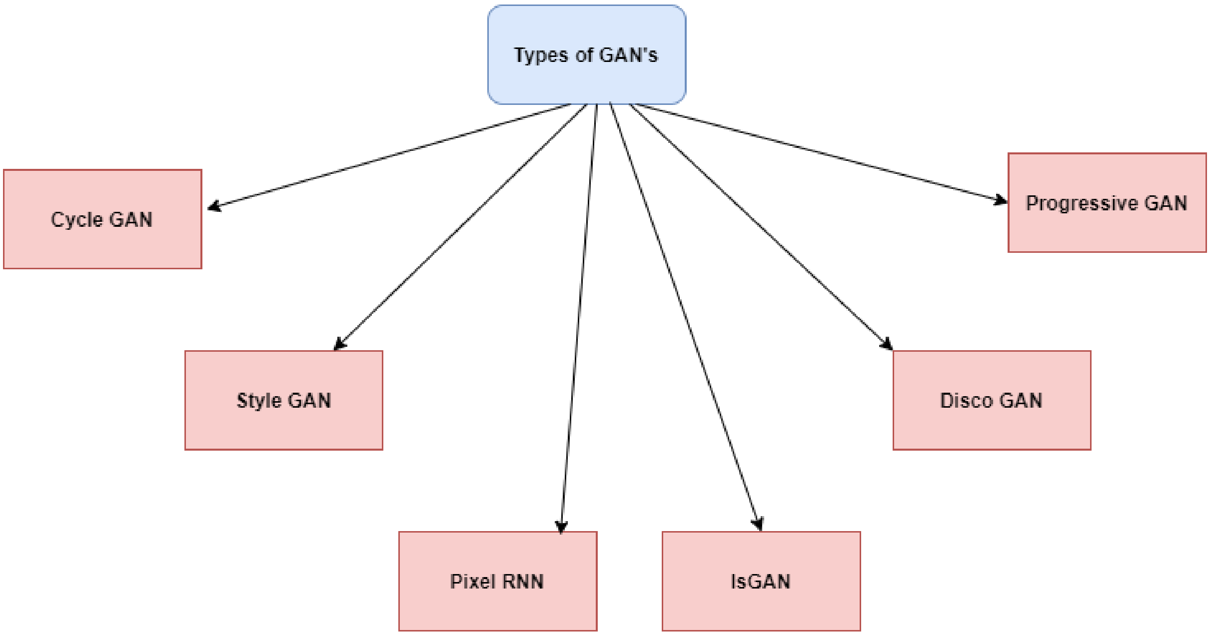


Fig. 1 Categorization of GANs

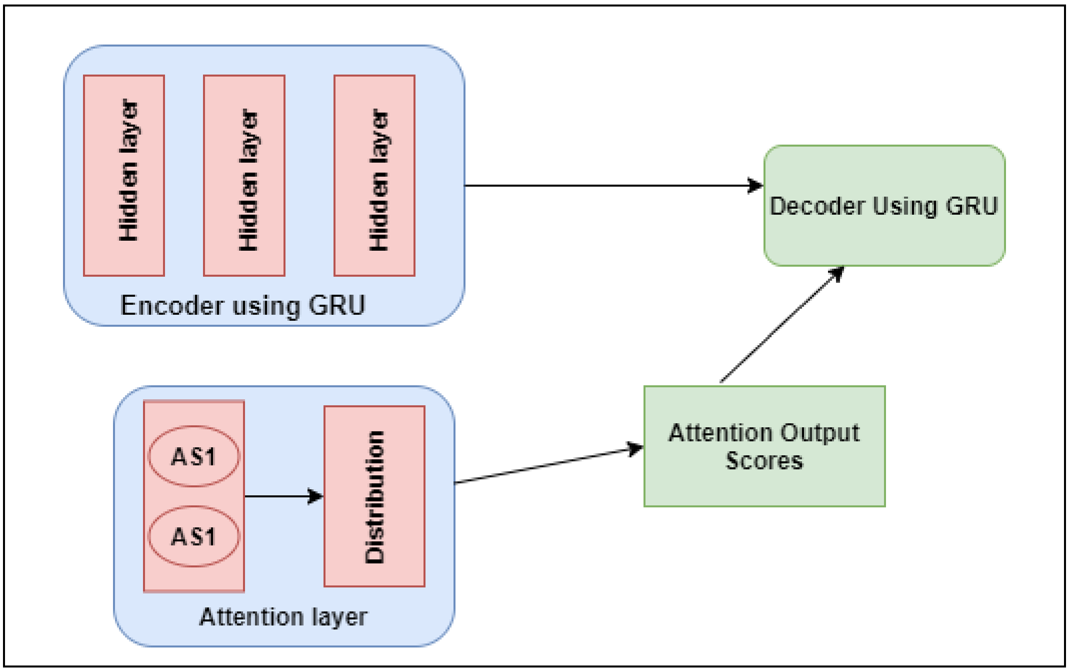


Fig. 2 Architecture of EAD for Summarization

2. Literature Survey

[1] In the internet era, many fraudsters spread various fake news over a particular trending topic that makes people believe and follow them. But, unknowingly to many individuals, this fake news affects reality in many aspects. This paper has explained some real scenarios and conditions where many changes were also done and have caused an impact on the government as its results. By the author, the impacts of such news have resulted in the development of AI-driven tools that could detect and eradicate them at the beginning thus, by avoiding its growth over the internet and causing many effects. This research has developed an FND- SCTI framework that initially focuses on picture representations using a VGG model. The outcomes are later helpful in advancing the training of text representation and are later subjected to an autoencoder that learns from the text and visual data given. Finally, the developed frameworks are combined to train a fake information detector. The developed model showed 83.9% accuracy.

[2] According to the author, recently, we can see a wide spread of fake news over multiple social media platforms irrespective of the context. The strategy of this fake news generation is to spread their posts, links, images

etc. Regretfully, many people become impacted by its similarity to the original news, and no one could easily identify its true nature. Eventually, due to widespread fake news and misleading individuals with inappropriate data, it became complex to identify such news, especially over social media as it is a shared media platform. This research aimed to find out such activities on facebook, a social media platform, and as said, have included a few more aspects like the user's interests and their interaction regarding other news to generate a particular reason. This research developed an automatic detection system of fake news in the chrome environment. Different properties were considered in this mechanism to analyze the trends using DL techniques that attained 93.4% of accuracy.

[3] The developers here urge the seriousness of rising issues with the fake news regarding many social platforms and the users misleading to it. Although many standard strategies were implemented to control these, they include some drawbacks, as stated by the author. Many approaches were developed to predict false content in deep training processes using hand-crafted retrieval techniques. However, the preceding constraints may apply to these techniques: (1) lack of usage in multi-modal backdrop information to improve the identification of false news and collect supplementary greater information in each of the media; (2) disregard to a great extent the entire hierarchy of textual content to support the development of improved news. So, an HMCAN framework was developed that focuses on understanding the context of the text by following its semantics in a hierarchal approach through BERT and ResNet models. Later, these outcomes were again fed into a network that could explain the contexts of the text and, gradually, an encoding structure that observes the semantic-rich text.

[4] By the author here, fake news not only imprint false statements on the public but also is the reason to misguide them by trapping them to their needs. Even though many models with standard technologies like CNN, RNN and other combinatorial algorithms were developed aiming at fake news identification, they could not work out the pre-processing of data that have shown rapid improvement. Depending on this, the current research developed both textual and visual modules to calculate the performances over the combinatorial type of data through CNN. The researcher stated that they had explored various layers of features inside the text and pictorial information. We can see the categorization of these CNN layers if they have only hidden characteristics and analyze what kind of visual is expected for the appropriate delivery of false news. They have presented a Coupling ConvNet multimodal framework, which merges data units and accurately detects news online according to its topic. A combinatorial study was performed in which the text-based CNN derived a highest of 96.26% accuracy.

[5] This research paper aims to mitigate the spreading of fake news and recognition of false photos distributed across social media as it is vitally essential. Fake pictures are software-modified altered pictures to misrepresent the content they communicate. Linguistic data are commonly linked to fake pictures. Through visual and spoken extracting features, a multi-modal structure is used. However, there are relatively few multi-modal designs; they rely on supplementary activities to find the association between different types. This research proposes an effective, multi-modal technique that recognizes fraudulent photos of sites for blogging. For processing images and phrase transformers, the approach utilizes the explicit CNN model EfficientNetB0.Fabricated pictures are predicted by dense layers and merged to allow for an integration of visuals and text. To evaluate the perfectness of the model, relative evaluation strategies were used that showed a prediction of 85.3% and 81.2% over different datasets.

[6] Here, the author has explained the risk of spreading fake news and its impact on people. Usually, such bogus news was spread by some individuals over the trending concepts to attract people to follow them. As this news would be identical to the original information, identifying them would be very difficult. The developers here have proposed a unique method to perform calculations over data by combining the multiple outcomes of a single combinatorial algorithm to transform it or make it look like an outcome from a multimodal representation. The data experimented with here regards both linguistic data and visual information. A pre-learned BERT and the picture properties extracted from the VGG-19 data were modelled on a picture-based dataset to retrieve the properties of the represented image. The score for these images is calculated collectively in a matrix that regards the images' weights and other properties to attend to its every detail that has attained a greater performance in the accuracy of the system up to 81.2 %

[7] Mingxi Cheng et al. implemented GAN's method for detecting fake news. It was mainly focused on detecting the rumours and giving the explanation for that rumours. Rumour text or images have been converted into binary format, and because of this system would face an explanation challenge. In the olden days, detecting rumours was done by the hand-crafted method. It needed more technical skilled humans, but now with the help of the AI system, it can easily and automatically detect which is rumour and which is not. Sometimes, AI systems don't wait for the verified database, but it was concluded from trending tweets only. GAN is the best latest version for detection. It is mainly used in images and videos, but here in this paper, they are mainly focused on text format. It's a little difficult to use GAN for text and to retrieve this problem, and there are different ways of approaching Gumbel-soft wax, WGAN, and RL. They proposed GAN-based frameworks to solve the problems faced in the past methods such as text level rumour detection and gene classification using mutation detection. They combined

GAN with RL for better results, higher quality and training as RL can be used for bigger sentences compared to other methods. They are performed on clean samples only. As mentioned above, the system can explain the rumour based on tweets by using the GAN method and then modify it slightly after receiving the verified data. The layered structure that they had put forward avoids function mixture and performance.

[8] Bing Han et al. introduced a new method called learnable SRM, which helps us detect fake news. Modern fake news is known as the deepfake. The existing detection techniques were inaccurate and did not handle low-quality data. So here, they proposed a new two-stream network for detecting thought learnable SRM. The first stream had RCB information and helped us know the semantic instability, and the second one parallelly handles the noise features extracted by SRM. Deepfakes are of 3 types: Expression fake, face2 face and face swap. And it is very hard to identify the difference between the fake and the real. The earlier system used the CNN methods to help the technical persons to differentiate the fake ones, but it’s been difficult regarding the low-key quality. 3D ConvNet has been used before for decoding videos and images for knowing, but in the case of highly compressed videos, the video or the image will be in a blur. So they used a TSN architecture in the optical flow stream by aiming for accurate spatial.

[9] Karthik Puranik et al. implemented the BERT concept with the BiLSTM model. Here they were mainly focused on the recent pandemic COVID-19. There is and is much fake news generated daily, and the most difficult task is to differentiate between fake and real news. They had considered social media websites such as Facebook and tweet. Here they were using domain-specific language models for detection. They had taken 3 factors: Rumor detection, fact-checking and stance detection. The model has already been predefined based on news out to society. For example, if they have one statement to differentiate this model, it would use the WHO and many other predefined statements compared to those posted on social media. BERT, DistilBERT, ALBERT. These are some of the models that they compared. BERT: used for the small predefined database. And compared to BERT, DistilBERT was used for the larger data, and here they used this as their model. They had a BiLSTM layer and saw some drastic changes in accuracy.

[10] Soumya Sanagavarapu et al. implemented the concept of multitask learning with BiLSTMCopsNet. LSTM was the best algorithm, but it faces challenges using a larger dataset. So, here in this model, they had used a BiLSTM model, which means two LSTM combined to recover from the problem they were facing. The CapsNet model was also used for the classification. It helps the model in dividing the conceptual learning into capsules. These capsules are loaded with inputs and help in encoding into fixed vectors. And these fake vectors may occur anywhere in the sentence by the BiLSTM would identify them easily. This multitask learning would help by collecting the data, subdividing them, performing the BiLSTM and CapsNet methods, and recombining them to know the real and fake news. Here one BiLSTM network works with the title, and the other work with the articles.

[11] Razvan Andonie et al. integrated the machine learning concepts with fake semantic news. They were focused on the small text to increase the accuracy. To build the relationship between the entities, they followed 3 steps: Metadata collection, Relation extraction and embedding. They had taken 2 important factors for expanding fake semantic news: the idea of scores and the percentage of truth. These steps would help in knowing the personal history and knowing the truth.

Table 1. Limitations of Previous Research Works

S.NO	Author Name	Algorithms used	Merits	Demerits
1.	Zeng	VGG, FND-SCTI	The outcomes from the frameworks were also subjected to an autoencoder that learns from the text and visual data from the given data.	In future, image editing procedures with DL like GANs can be implemented.
2.	Sahoo	KNN, SVM, LR, DT, NB, LSTM and BiLSTM	Robust System	Boosting algorithms can be implemented further.
3.	Qian	HMCAN, BERT and ResNet	Included and worked almost on all the existing limitations with the standard procedures.	Further developments include additional information gains and visual content.

4.	Raj	CNN	Various layer-wide studies were performed as a deep introspection to find the best acting method.	Hyper tuned parameters could be used next.
5.	Singh	CNN - NetB0	Shown a better performance than standard methods in real-time.	Text included images, sarcastic images and adversarial pictures were not considered.
6.	Tuan	BERT and VGG-19	Worked on combined features in text that also finds out the relations among the modalities.	Further, user specifications can also be included and processing multiple images simultaneously.
7.	Mingxi Cheng	LSTM,CNN ,GAN	It gives us an explanation even without the verified data.	Sometimes the explanation can be different from the real news.
8.	Bing Han	Learnable SRM	It can be used in any application to gain better accuracy as it has 2 streams.	It can have more explanation restrictions, and the application scope
9.	Karthik Puranik	BiLSTM	It had bi LSTM where the work has been divided and done in a better way and with better accuracy	They are particular on a single application and also only in text format
10.	Soumya Sanagavarapu	BiLSTM, CapsNet	Work has been divided and then given to BiLSTM for better accuracy.	NLP can be used to avoid dynamic differentiation of articles by high-level analysis.

2.1. Gaps Identified

From the survey table, the proposed research has identified the following gaps to be addressed to build a successful model.

1. Construction of new images with simple data augmentation techniques is complex and expensive.
2. Since the images involve text for detecting fake news[21], the involvement of text processing techniques alone can't make the extraction process easier.
3. The usage of synthetic analysis is successful for implementing shorter text and where the modification of meaning doesn't impact the news.
4. Designing CNN involves a static environment, which is adjusted using brute force techniques.

2.2. Novelty

In the proposed system, GAN's are implemented using the concept of parallelism, in which the text is extracted from the images, and new images are created based on this extraction. While working with text, it doesn't only check synthetic analysis. It also considers semantic analysis to preserve the meaning and keep the essential words in their place. This is an integrated approach where it uses a pre-trained model for text extraction and GAN's for the creation of the new image.

3. Proposed Methodology

Most of the older systems have increased their size of datasets by performing basic image manipulation techniques, popularly known as "Data Augmentation". But due to inefficiency and many operations involved in manipulations, researchers have started thinking about the utilization of GAN's in the past few years. GAN is a two-step approach to creating more images which are more related to the given dataset. The below section explains the two major components of GAN. Among the existing GAN's, the best GAN to convert the images is "Cycle GAN". The major goal of any Cycle GAN structure is to create relevant images in different styles. A function is defined in such a way that it maps the political images with celebrity images, i.e. f(P)→f(C), a cyclic loss function is defined to perform both mapping and inverse mapping to do two types of the training process. This training process involves learning from paired images as well as learning from not matching images. These functions try to convert political images into celebrities and celebrities into political images. The process of reconstructing the images can be defined as shown in equation (1)

$$\text{Loss\_Function}(Pol, Cel, D_P, D_C) = \text{Loss\_incurred}(Cel, D_C, P, C) + \text{Loss\_incurred}(Pol, D_P, P, C) + \alpha * \text{Loss\_incurred}(Pol, Cel) \quad -(1)$$

Where,
Loss_incurred(Cel, D_C, P, C) represents the loss function incurred by celebrities by misclassifying the politicians as celebrities

Loss_incurred(Pol, D_P, P, C) represents the loss function incurred by politicians by misclassifying celebrities as politicians

The Cycle GAN consists of two generators and two discriminators, in which one generator takes input from politicians, and different images are considered as input by the second generator. There is a component called "Cycle Consistency", which means that output from one generator can act as input to the second generator to match the dataset images. Since it is a cycle, the output of the second generator can be sent as input to the first generator. The major constraint of Cycle GAN is that both conversions should be successful, computed using the LOSS Function, which finds the difference between the generated outputs and inputs in both stages. So, GAN systems call them "Regularization Parameters".

3.1. Sequential Generator

This step takes the input in the form of feedback from the discriminator. It tries to deviate from the discriminator and classify it as a real image rather than a fake one. The generator gets trained from some random inputs of the dataset in the form of noise to create different nearest probable images, and all these images are converted into data points on the co-ordinator space and compute the loss function to find the penalties that are caused during the process of failing to cheat the discriminator. The generator supports the backpropagation concept during the training phase. The random space containing the noise input is known as "Latent Space". To optimize the workflow, it defines an objective function minimizes, as shown in equation (2).

$$\textbf{Loss\_Cycle\_GAN}(G, D_p, C) = \frac{1}{n} * \sum_{i=1}^{n} \left(1 - D_p(G(C_i))\right)^2 \quad - (2)$$

Where,
n represents the number of images in the dataset
G represents the number of generated images
D_p Denotes discriminator-identified politician images count

Cycle GAN loss should be minimized by designing the layered architecture for both the components of Cycle GAN, as shown in figure 3. The figure highlights only two design layers as a sample to get a completed overview of different layers.

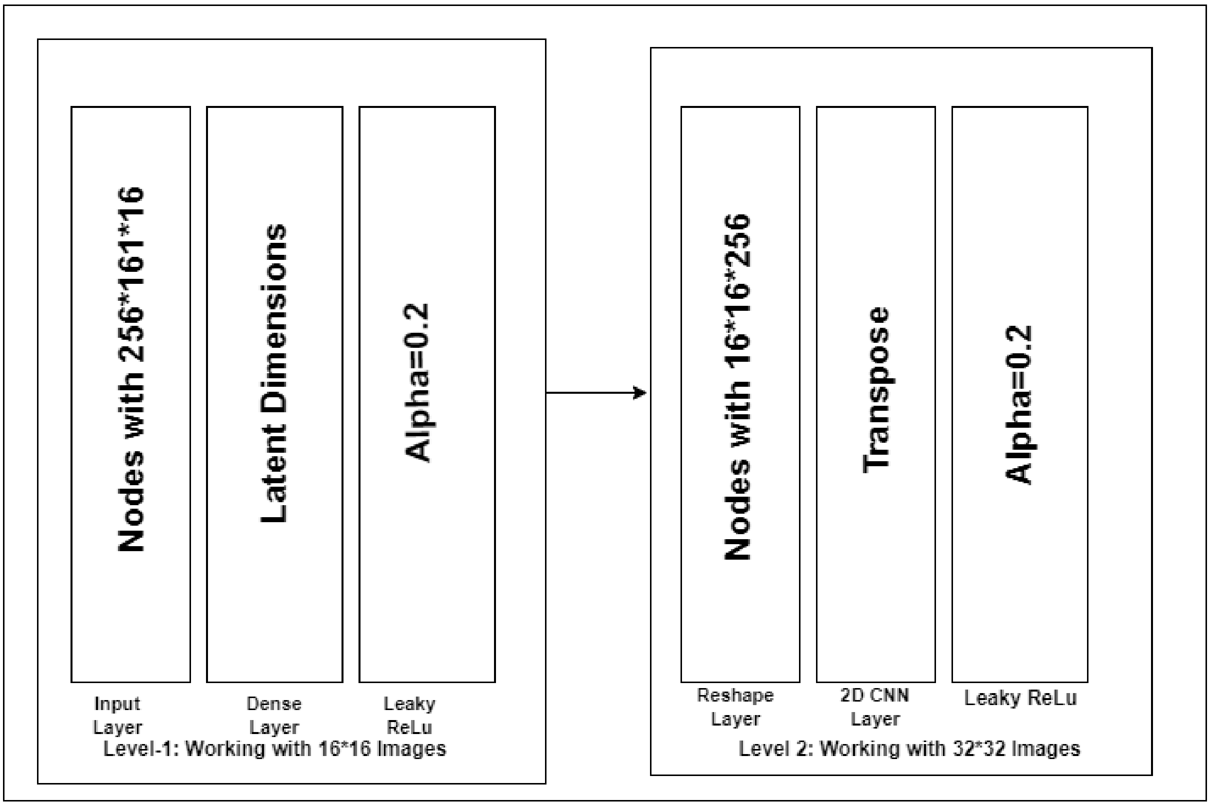


Fig. 3 Sample Design of Generator Module

3.2. Sequential Discriminator

This component acts as a "Classifier" to differentiate between the original images and images created by the generator. To train the neural networks, it produces the random weight using the concept of backpropagation. In discriminator, for real images, it produces the output as 1; for fake images, it produces the output as 0. In this phase, it takes 128*128*3 images as input and implements Leaky ReLu as an activation function, shown in equation (3) to produce 64*64 images as input to the next 2D convolution layer.

$$f(input) = 1, \quad if\ input < 0$$
$$= \beta * \text{input}+1, \text{ if input}>=0 \text{ - (3)}$$
Where β is a small constant

The model contains 4 convolution layers and reduces the size to 8*8, and at last, for classification purposes, it uses a dense layer with adam optimizer, shown in equation (4). Adam optimizer computes nth moment to adapt to each weight and generates a good training model

$$Momentum_n = E(Weight^n) \text{- (4)}$$

The reduced filter size for the next layer is computed as shown in equation (5)

$$\text{Reduced\_filter\_size} = \left(\frac{W-K+P}{S}\right) + 1 \text{ – (5)}$$

Where,
W represents Image Width
K denotes the number of kernels in input and other layers of CNN
P represents padding cells in the image
S denotes stride size

$$\text{Kernal\_size} = \left(\frac{128-3+5}{2}\right) = 64$$

Figure 4 explains the computations at 2D convolution regarding the training parameters using equations (6) & (7).

Number of training parameters produced by first layer=(k_size*k_size*nc*nfb)+nfb – (6)

Where,
nc represents the number of channels
nfb denotes biased filters count
Therefore, the Discriminator generates
Number of training parameters in the first layer =(3*3*3*64)+64= 1792
Number of training parameters produced by second layer=(k_size*k_size*nc*nfb*pf)+nfb- (7)
Where,
pf represents the number of filters in the previous layer
Number of training parameters in the second layer= (3*3*3*64*32)+32= 55,328

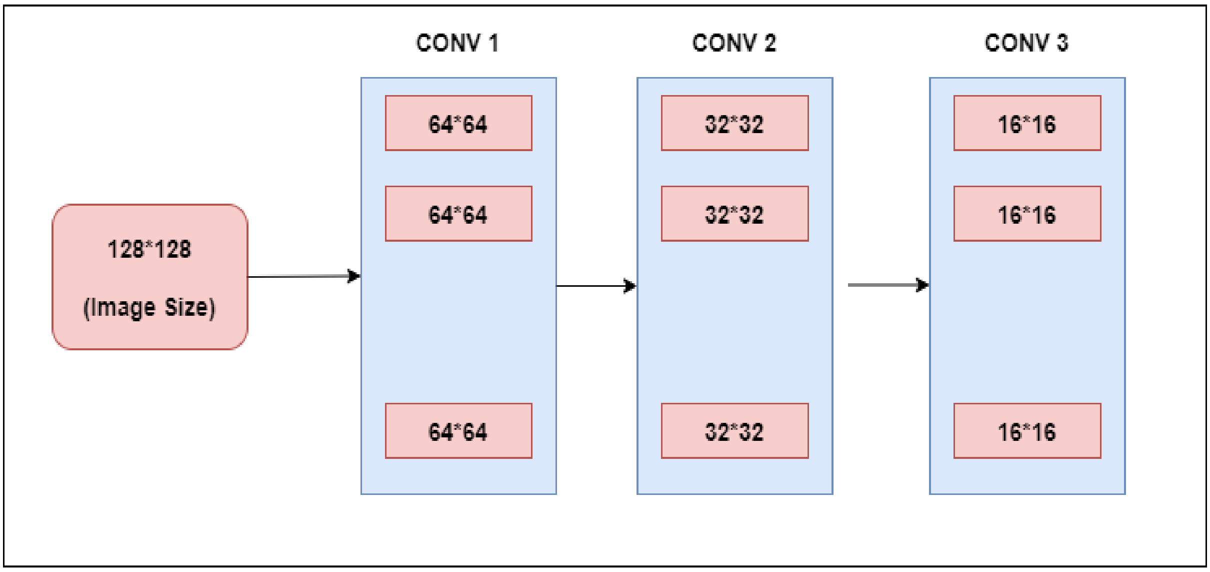


Fig. 4 Reduction of Filters From Layer to Layer

This model uses LSTM encoders and decoders with a customized embedded layer to pre-process the data to extract the text. The power of LSTM lies in its capability to learn long sequence data with temporal dependencies. The encoder neural network takes the input as text, which extracts from images and converts them into a latent vector with proper, good and unambiguous text. The decoder produces the target text by utilizing the pre-trained model known as "PEGASUS", which is popularly used for performing abstractive summarization on the input data. It uses sequence2sequence, which gets automatic training to map the input sequence with the output sequence. The main goal of this self-pre-trained model is to produce gap sentences to fine the summarization model. It marks the important sentences by computing the similarity measurement known as "ROGUE-N". N-gram combines a group of words, and ROGUE-N checks the number of matching "N-grams" by comparing the generated text with training text. It calculates three metrics associated with it, as shown in equations (8a), (8b) and (8c). ROGUE-N-Recall computes the overlapping input and output texts of N-grams based on input.

$$ROGUE - N - Recall = \frac{count\ of\ n-grams\ in\ both\ input\ and\ output}{count\ of\ n-grams\ in\ input} \quad \text{- (8a)}$$

Sometimes the computed recall may generate a 100% value, which means it is not a fine-tuned model. So, to overcome this issue, it computes another known as "ROGUE-N-Precision", which computes the overlapping based on the output.

$$ROGUE - N - Precision = \frac{count\ of\ n-grams\ in\ both\ input\ and\ output}{count\ of\ n-grams\ in\ output} \quad \text{- (8b)}$$

The ROGUE-N-F1Score is a weighted average of the above two metrics, and it is a reliable measure because it identifies many words and discards many irrelevant words.

$$ROGUE - N - F1Score = 2 * \left(\frac{ROUGE-N-Recall * ROUGE-N-Precision}{ROUGE-N-Recall + ROUGE-N-Precision}\right) \quad \text{- (8c)}$$

In this sequence2 sequence, the model is divided into two parts. The encoder tries to compute the context vector for the input text and generates a numerical representation for the corresponding text. The decoder tries to find the summarized data based on the context vector produced by the encoder.

Recurrent Neural Networks have a disadvantage because of the short memory capability. So, to hold the longest texts in the fake news detection, the model implemented LSTM, which supports the longest sequence and does not suffer from gradient vanishing. These networks contain gates to store the information, filter the irrelevant information at each stage of the layer, and pass it to the next gate to make good predictions. The main advantage of LSTM and GRU networks is that instead of remembering the entire sentence, it keeps data about only important keywords like positive or negative words about a review. All the gates operate with the help of the sigmoid function, which is described in equation (9) to get the output as either 0 or 1 and, in turn, helps layers to get either updated or forgotten data.

$$f(feature) = \frac{1}{1+e^{-(feature)}} \quad \text{- (9)}$$

It implements three gates to complete the proposed model, and these are discussed below section.

i. The first gate it implements is forgetting to filter the data as important or not. Since it uses the sigmoid function, it discards the data if the value is approximately zero; otherwise, it forwards to the next gate, assuming it is important.
ii. The second gate is input; it receives input from hidden states and current inputs from the training model. This gate performs point-wise operations to get the new cell state values.
iii. The third gate, i.e., the output gate, decides the information be maintained in the hidden states.

The overall architecture of the proposed model is illustrated in figure 5.

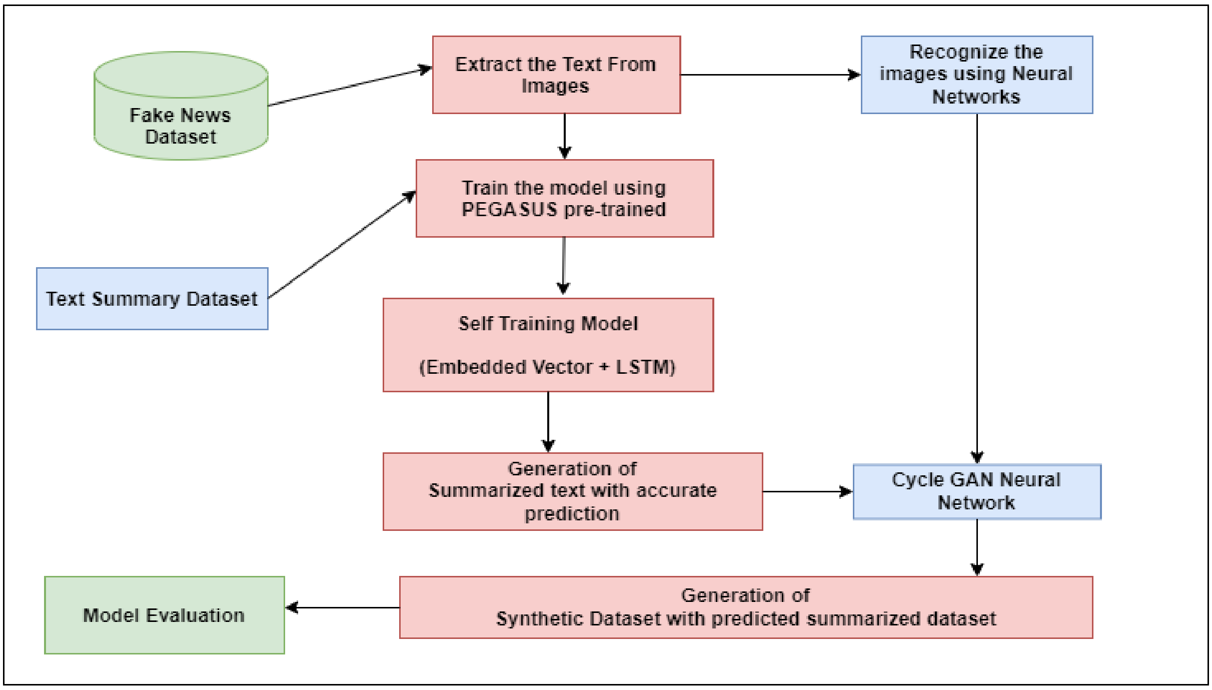


Fig. 5 Brief Overview of Proposed Research

4. Results and Discussion

GAN's are popular for creating synthetic images. In the proposed research, the texts are extracted from images and based on the summarized data, new images created by enhanced GAN's are shown in figure 6.

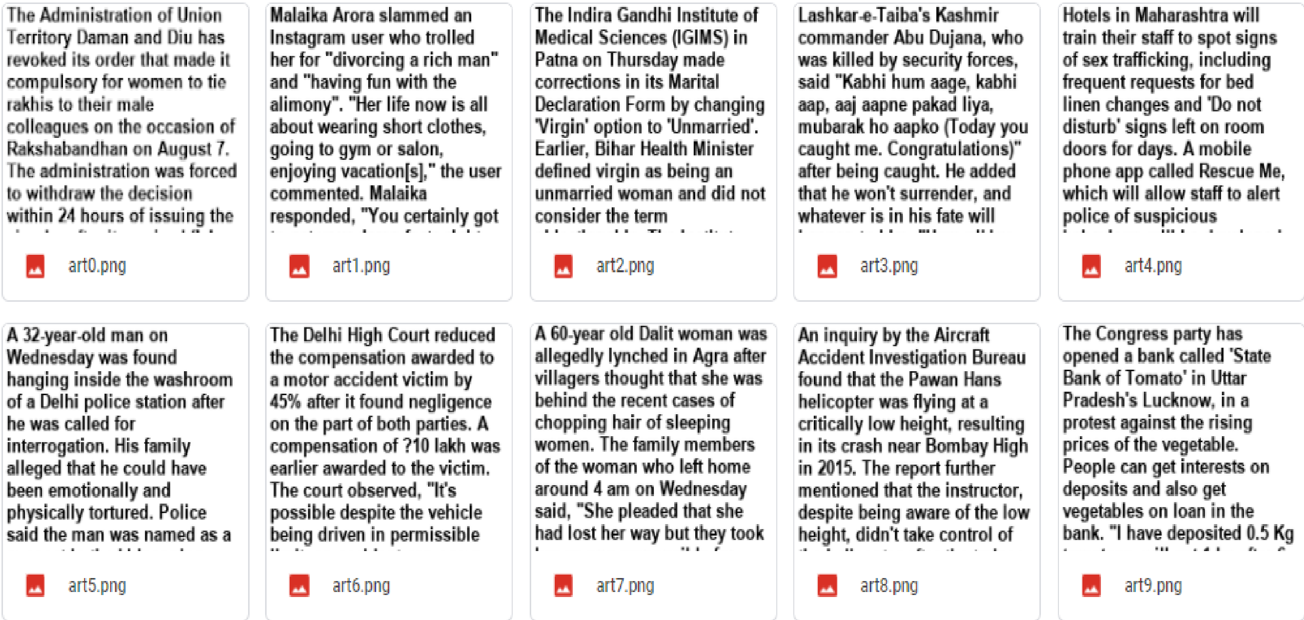


Fig. 6 Created Synthetic Images

These created synthetic images resemble real images and try to cheat the discriminator during the classification process. Deep learning algorithms are efficient only when they can make huge amounts of data. These images increase the size of the dataset during the process of training. Table 2 shows sample outputs of summarized text predicted using pre-trained and self-trained models.

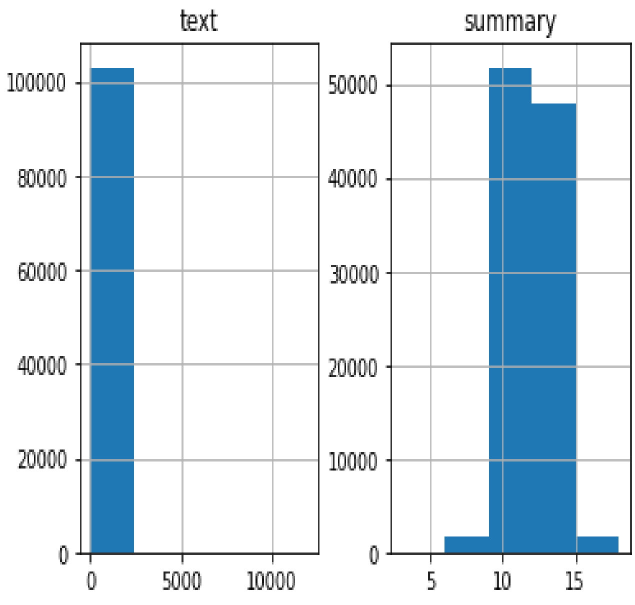
Table 2. Sample Predicted Text Outputs

S.No	Review Text	Summarized Text	Predicted Text
1	Frances Fitzgerald, the deputy prime minister of Ireland, announced her resignation on Tuesday to prevent the government's collapse and a potential snap election. She resigned hours before the main opposition party proposed a motion of no confidence against her. The political crisis started over Fitzgerald's role in the police whistleblower scandal.	Irish deputy prime minister resigns to avoid govt collapse end	Pm Modi appointed as new president end
2	On Sunday, rj wicketkeeper-batsman jos Buttler scored his fifth consecutive fifty in the IPL 2018 to tie the record of most consecutive 50-plus runs in the IPL held by veteran Indian cricketer Virender Sehwag. Sehwag accomplished the feat when playing for dd in the ipl 2012; Buttler is just the second batsman (after Shane Watson) to knock two consecutive 90s in the league.	Buttler equals Sehwag's record of most straight 50s in ipl end	Rohit Sharma becomes highest ever score in ipl history end
3	On Wednesday, Maruti Suzuki India announced that it is recalling 640 units of its Super Carry mini trucks sold in the domestic market due to a potential fuel pump supply defect. The automaker said that the recall affects Super Carry units produced between January 20 and July 14, 2018, and the affected vehicles' faulty parts will be replaced free of charge. Beginning Maruti recalls its small vehicles due to a fuel pump problem in India and ending	Maruti recalls its mini trucks over fuel pump issue in India end	India to build its car with electric cars end

```
_____________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
=============================================================================================
input_1 (InputLayer)            [(None, 100)]        0
_____________________________________________________________________________________________
embedding (Embedding)           (None, 100, 200)     5927600     input_1[0][0]
_____________________________________________________________________________________________
lstm (LSTM)                     [(None, 100, 300), ( 601200      embedding[0][0]
_____________________________________________________________________________________________
input_2 (InputLayer)            [(None, None)]       0
_____________________________________________________________________________________________
lstm_1 (LSTM)                   [(None, 100, 300), ( 721200      lstm[0][0]
_____________________________________________________________________________________________
embedding_1 (Embedding)         (None, None, 200)    2576600     input_2[0][0]
_____________________________________________________________________________________________
lstm_2 (LSTM)                   [(None, 100, 300), ( 721200      lstm_1[0][0]
_____________________________________________________________________________________________
lstm_3 (LSTM)                   [(None, None, 300),  601200      embedding_1[0][0]
                                                                 lstm_2[0][1]
                                                                 lstm_2[0][2]
_____________________________________________________________________________________________
time_distributed (TimeDistribut (None, None, 12883)  3877783     lstm_3[0][0]
=============================================================================================
Total params: 15,026,783
Trainable params: 15,026,783
Non-trainable params: 0
_____________________________________________________________________________________________
```

Fig 7. Compiling the Number of Trainable Parameters

Figure 7 represents the output for the computation trainable parameters using the transfer learning in which the Pre-trained model known as "PEGASUS" as the initial layers of models, and the remaining layers are customized using LSTM and Embedding vector layers. The main goal of the embedding layer is to take care of the pre-processing automatically by the neural network layers. Figure 8 shows the accuracy of the cleaned text and generated summary extracted from the original text. It is observed that the model has obtained 95.78% accuracy at this step.




```
cnt = 0
for i in pre['cleaned_text']:
    if len(i.split()) <= 100:
        cnt = cnt + 1
print(cnt / len(pre['cleaned_text']))
```

```
0.9578389933440218
```

Fig. 8 Accuracy Computation for Cleaned Summary Text

Figure 9 represents the accuracy and loss values obtained by the model in each iteration. Here, the batch size is assigned to 128, epochs are adjusted to 10, and every time the model tries to save the best result as .h5 series.

```
Epoch 1/10
250/250 [==============================] - 1s 2ms/step - loss: 18.2188 - accuracy: 0.9384
Epoch 2/10
250/250 [==============================] - 0s 2ms/step - loss: 2.3609 - accuracy: 0.9787
Epoch 3/10
250/250 [==============================] - 0s 2ms/step - loss: 2.0559 - accuracy: 0.9880
Epoch 4/10
250/250 [==============================] - 0s 2ms/step - loss: 1.4148 - accuracy: 0.9895
Epoch 5/10
250/250 [==============================] - 0s 2ms/step - loss: 1.3929 - accuracy: 0.9905
Epoch 6/10
250/250 [==============================] - 0s 2ms/step - loss: 0.7228 - accuracy: 0.9910
Epoch 7/10
250/250 [==============================] - 0s 2ms/step - loss: 0.7470 - accuracy: 0.9900
Epoch 8/10
250/250 [==============================] - 0s 2ms/step - loss: 0.9537 - accuracy: 0.9918
Epoch 9/10
250/250 [==============================] - 0s 2ms/step - loss: 1.1261 - accuracy: 0.9916
Epoch 10/10
250/250 [==============================] - 0s 2ms/step - loss: 1.2691 - accuracy: 0.9923
```

Fig. 9 Accuracy and Loss values obtained in each epoch during the training phase

Table 3. Evaluation Metrics

S.NO	Author Name	Algorithms used	Accuracy	Recall	Precision
1.	Zeng	VGG, FND-SCTI	83.9	81.4	80.1
2.	Sahoo	KNN, SVM, LR, DT, NB, LSTM and BiLSTM	93.4	92.1	92.1
3.	Qian	HMCAN, BERT and ResNet	90.8	89.5	88.6
4.	Raj	CNN	96.26	94.7	94.1
5.	Singh	CNN - NetB0	85.3	83.9	82.4
6.	Tuan	BERT and VGG-19	81.2	81.2	81.2
7.	Mingxi Cheng	LSTM,CNN ,GAN	72.69	71.8	70.3
8.	Bing Han	Learnable SRM	90.36	90.1	89.5
9.	Karthik Puranik	BiLSTM	98.22	98.1	98.1
10.	Soumya Sanagavarapu	BiLSTM, CapsNet	97.96	95.3	96.1
11.	Razvan Andonie	CNN, SRM, LSTM, BiLSTM	90.25	89.2	89.7
12.		Proposed Model	99.23	97.34	97.79

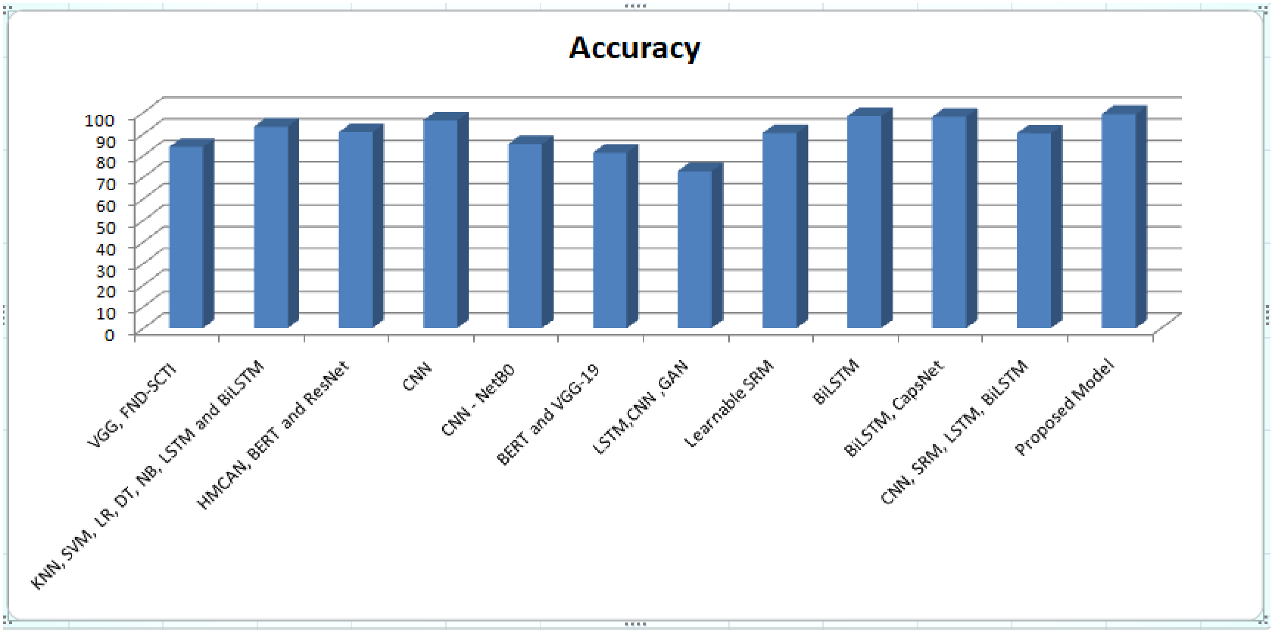


Fig. 10 Accuracy Evaluation based on Previous Works

In figure 10, X-axis represents the names of the algorithms and Y- the axis represents the accuracy rate. Compared to the existing works, the accuracy obtained for the proposed model is high, and all remaining models have above 90% accuracy. Still, every model cannot be evaluated with accuracy alone. The remaining section of the paper discusses the other metrics. Accuracy is measured as the ratio of correctly classified images concerning the total number of available images. Since the model has obtained 99.23% accuracy, the remaining is considered a loss, i.e., the loss rate is negligible. The system has improved nearly 1% better than the BiLSTM, which has proved its efficiency in accessing the sequential data.

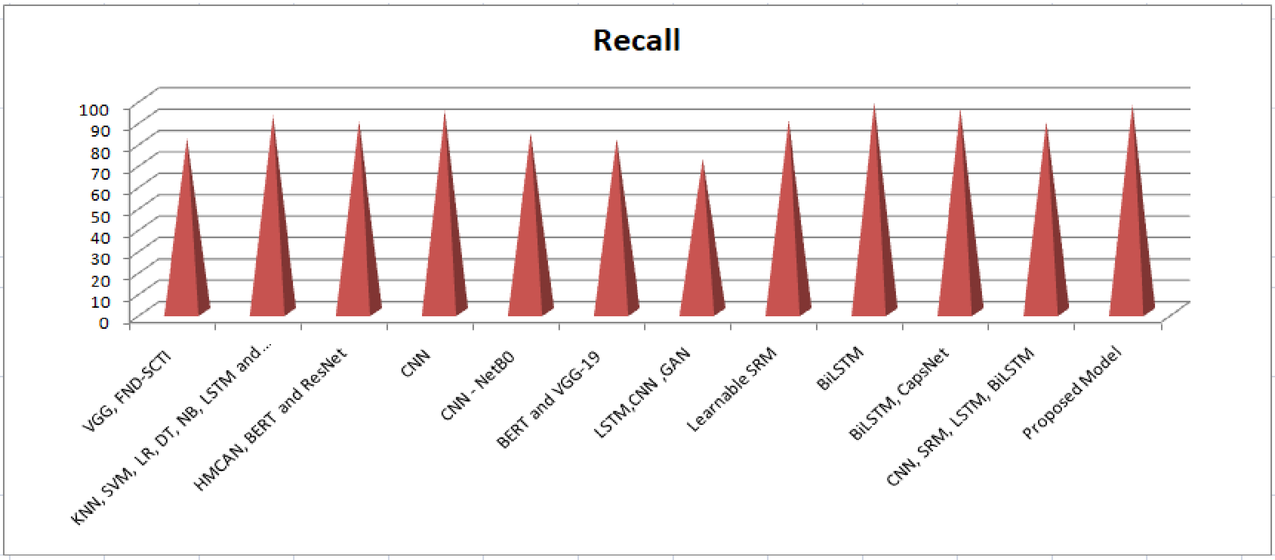


Fig. 11 Recall Analysis of various approaches

The dataset utilized in this proposed system is the imbalanced dataset. So, along with accuracy, the proposed model also focused on the Recall metric. Figure 11 discusses "Recall", the value exhibited by the existing approaches and the proposed model. It tries to measure the positivity rate by computing the ratio of correct positive classification concerning the total number of positive images available in the data. It has achieved a 0.07% less efficient rate than the other model.

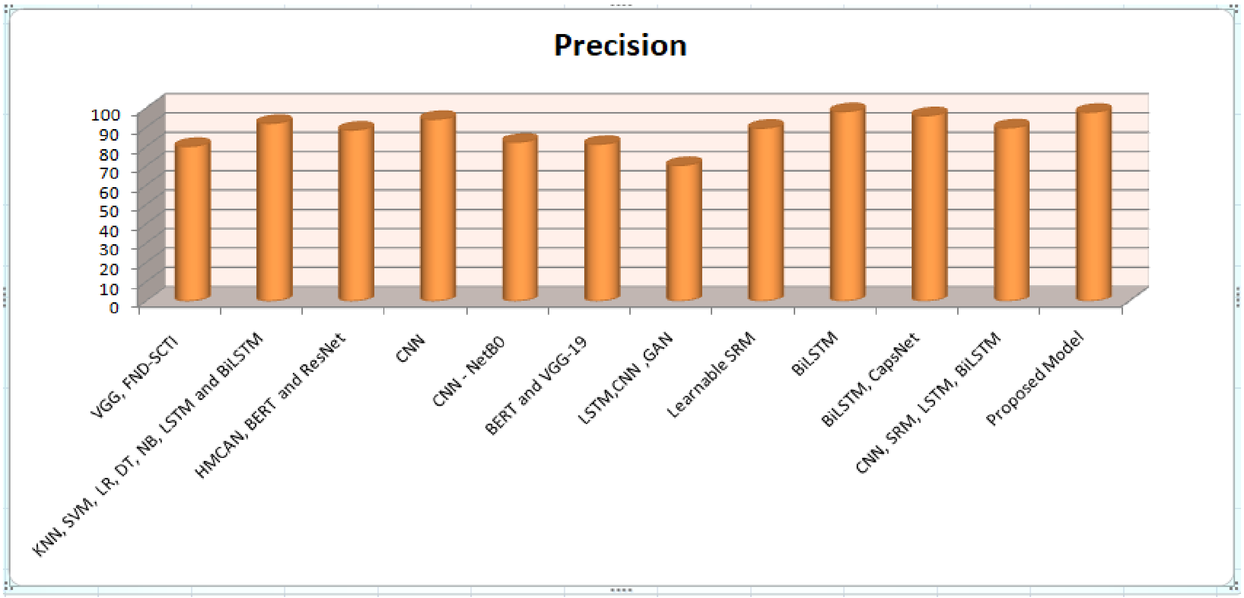


Fig. 12 Analysis of Performance based on Precision Parameter

Figure 12 represents the precision, which computes the positivity rate as the ratio of correct positive labels concerning the classified positive samples in the dataset. The model has got 0.002% less efficient when compared to the CNN models.

5. Conclusion

The proposed research from the literature survey majorly identified that using simple GAN has a drawback of creating less synthetic data because of the image association with text. Even LSTM's suffer from confidence levels because their efficiency lies in text handling rather than images. So, the proposed research implemented an integration mechanism that has efficiently worked with images and text. The proposed system created a pre-trained model known as "PEGASUS", which extracts the text and computes the summarized text by finding their respective scores. It also considers the context and significance of shortening the text and projects relevant data in different environments. Most social media platforms spread the news using multimedia files. Hence, the proposed research wants to create synthetic data based on the text extracted using the enhanced cyclic GAN, which computes its loss function based on the news category. In future research, the model tries to extract the features using the enhanced autoencoder and decoder mechanism, which helps in dimensionality reduction.

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