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RESEARCH ARTICLE

Fake News Detection System Using Featured-Based Optimized MSVM Classification

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ABSTRACT Fake News creates erroneous suspense information that can be identified. This spreads dishonesty about a country's status or overstates the expense of special functions for a government, destroying democracy in certain countries, such as in the Arab Spring. Associations such as the "House of Commons and the Crosscheck project" address concerns such as publisher responsibility. However, since they rely entirely on manual detection by humans, their coverage is minimal. This is neither sustainable nor possible in a world where billions of items are withdrawn or posted every second. The paper produces a deep study on past research work on fake news detection on the selected data-sets and proposes an algorithm with Multi-layered Principal Component Analysis for feature selection followed by firefly-optimized algorithm. Multi-Support Vector Machines(MSVM) are finally used to classify the news. We used ten different data-sets for testing the proposed algorithm. As the number of features in the data-sets are more, feature extration and selection methods help to improve the accuracy in respective data-sets. Only the datasets having less number of features gave a lower performance on our feature extraction algorithms.

INDEX TERMS Fake news, rirefly, long short-term memory (LSTM), multi support vector machine (MSVM).

I. INTRODUCTION

The existing fake news detection methods suffer from different issues such as limited dataset and high computational cost. A fake news classification model task to determine whether a small amount of information is correct or incorrect is the fundamental instance of misinformation identification. However, the binary classifier approach is inadequate when the data is partially correct and partially false. False news detection also can be treated as a fine-grained multi-classification challenge by introducing multiple categories to data collections to tackle this limitation. The datasets supplied feature distinct Ground Truth Labels, and the regression construction gets difficult because translating the distinct labels to numerical scores appears to be a complex operation [1]. Therefore, there is a need for a methodology to overcome the existing issues

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Following the 2016 presidential election, as have saw in fig.1, the influence of "fake news" has been an enormous problem. Based on an extensive investigation of 126,000 verified and fraudulent news items on Twitter from 2006 to 2017, Vosoughi and colleagues revealed that fake articles spread more frequently and quickly than authentic news stories [2]. As stated by the critical theories on fake news in psychology and social sciences (see a thorough evaluation in Ref. [3]), the more a false news story spreads, the higher the probability of social media users spreading and believing it due to repeated exposure and peer pressure. Such levels of trust and beliefs may quickly be multiplied and perpetuated within social media thanks to its echo chamber effect [2]. Hence, a major investigation has been performed on effectively detecting fake news to prevent its transmission on Social Media. Fake news detection techniques may be commonly categorized into (1) content-based and (2) social-context-based tactics.

The primary difference between these two types of innovations is whether or not they revolve around social context information: the data on how the news has been shared on social media, where rich secondary research about people on social media engagement and their connections/networks can sometimes be exploited. Many unique and significant solutions (e.g., [2] and [4]) have been proposed to exploit social context information. As we can see in fig.1, after creation and publication, the most dangerous part is propagation. We need to stop fake news at its root before it spreads its branches, so we use fake news detection to stop this at the root by getting all the rooted information about it [78].

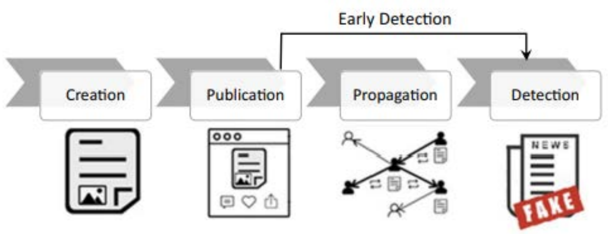

FIGURE 1. **Need of fake news detection [2].**

Nowadays, numerous kinds of algorithms [5], [6] are given for fake news detection jobs, including old machine learning-based and newer learned-in-the-classroom approaches. Traditional techniques [5] such as Support Vector Machine(SVM), Random Forest, and Decision Tree mainly depend on hand-craft features to disprove fake news. For instance, SVM-TS [5] leverages a linear classifier based on a Support Vector Machine paired with heuristic rules to label the postings as fake or real and adds a time-series structure to replicate the social feature variations. With the tremendous success of neural networks, modern deep learning-based models have gained higher performance than traditional ones, thanks to their great feature extraction capabilities. Some early studies aimed to identify features from explicit textual material to detect fake posts. Then it further used Recurrent Neural Networks (RNN) [7] and its variants, sometimes including Long-Short Term Memory (LSTM), to extract temporal language patterns for fake news detection. On this basis, another study adds the attention mechanism into RNNs and extracts the sequence language features of particular focus points. Also, several research suggests that convolutional neural networks (CNN) [8] train these exact high-level representations acquired from postings on social networking sites for identification.

To date, news material has advanced from pure text content to multi-modal content combining text, photographs, and videos. An implementation of multimodal is provided in Figure 1. Fakenews detection employing multi-modality has garnered considerable attention. Many initiatives [8], [9] employ deep algorithms to extract and integrate textual and visual democratic legitimacy in posts. However, sophisticated techniques that effectively integrate complementary and elongated multimodal information encompassing semantic notions and the individual's character to complement and enhance each modality may not have been substantially examined. For instance, some models [8], [10] automatically concatenate features extracted in different modalities, such as text and image, together to create the final representation. In [10], the authors present a multi-modal variational autoencoder (MVAE) to independently encapsulate and gather information about each modality and then deploy a fully connected network to accomplish multi-modal fusion. However, much critical information is concealed due to the learning self-aggregation technique and the limitation of completely connected networks. In addition, these algorithms cannot harness the different semantic content of textual material. Most state-of-the-art algorithms try to exploit the also before the BERT [11] model as translational feature extractors that rich feature depictions may be built by several layers. However, they broadly apply the characterizations of the corresponding output layer of the BERT model to accomplish false news detection, which cannot correctly leverage the initial hidden state to exploit the plentiful textual semantics.

The existing fake news detection methods suffer from limited datasets and high computational costs. The fundamental instance of misinformation identification is a fake news classification model task to determine whether a small quantity of information is correct or incorrect. However, the binary classifier approach is inadequate when the data is partially correct and partially false. False news detection also can be treated as a fine-grained multi-classification challenge by introducing multiple categories to data collections to tackle this limitation. The datasets supplied feature distinct Ground Truth Labels, and the regression construction gets difficult because translating the distinct labels to numerical scores appears to be a complex operation [1]. Therefore, there is a need for a methodology to overcome the existing issues [79].

So we have introduced our model in which we are using optimized MSVM algorithms with the help of feature attraction using PCA. The optimized firefly algorithm will make the feature selection. We have tester our algorithm on more than 8 number of different datasets, which includes some famous dataset FakeNewsNet, PHEME, LIAR, covid19 2020 twitter dataset, PolitiFact, ISOT, Weibo, and many more the performance we are getting on our algorithm is more reliable than any other algorithm which we are comparing in this article. In this article, first, we discuss the different model present in the market with multiple datasets, and we discuss where these algorithms are lacking in which our model is outperforming. We will discuss our model and implementation and the different dataset we have used and compare the performance results with other models. The fake news detection model's performance is measured by its accuracy, precision, recall, F1 score, etc. In the last section, we explained our conclusion and the result. So some principal contributions of this article are:

1) Machine learning-based system optimized MSVM is purposed for detecting fake news.
2) A python-based application is used to detect fake news on the given dataset of news article tweets or any other social media post.

3) Firefly and Principal Component Analysis's optimized version is used for feature selection and feature extraction in this system.
4) Experimented results show some improved accuracy than many existing models on ten popular datasets.

The paper is divided into seven sections. Section II briefs about various studies of Fake News detection using different datsets. Section III explains all the algorithms and methods used during our study, which are further connected in Section IV about our proposed methodology. Section V summarizes the experimental results and its analysis in section VI. Our study is summarized in Section VII

II. RELATED WORKS

With the advancement and variety of technologies, there are lots of proposed models which are using different technologies. Some of the literature papers use machine learning algorithms, some of them use deep learning models, and many use a hybrid of these both or use their models in multiple layers. We have studied and tested some literature papers with our models on different datasets as we have mentioned their accuracy. Also, concerning their dataset, we have made this table consist of references which will be helpful for the reader to get a better understanding and what technology they are using on which dataset and what accuracy they are getting through these models. After this table, we will discuss the limitations of these models, which is why our model neglects their cons. So, the overview of the comprehensive literature studies and their merits and drawbacks are provided in Table 1.

Fake news detection is divided into three parts of detection first is textual data, the second is image-related data, and the third is video-related data. There are lots of models used to detect fake news from all of these outcomes like in [19] blockchain and Bi-LSTM is used to achieve the highest accuracy in all of the given research articles for the dataset of PolitiFact, in Gossipcop which is a smaller dataset the CNN approach used by [38] is excellent in all the other research articles. On Twitter election dataset XLM-RoBERTa CNN approach is used in [50] is giving maximum accuracy among all the other models. On the FakeNewsNet dataset BERT approach is used in [35] is giving maximum accuracy among all the other models. On the BUZZFEED dataset ASSO-OSSIW approach is used in [23] is giving maximum accuracy among all the other models; on Weibo, the dataset CNN approach is used in [42] is giving consistent accuracy in every epoch among all the other models, on LIAR dataset NLP approach is used in [43] is giving maximum accuracy among all the other models, on PHEME dataset MN approach is used in [42] is giving maximum accuracy among all the other models.

A fake news classification model task to determine whether a small amount of information is correct or incorrect is the fundamental instance of misinformation identification. However, the binary classifier approach is inadequate when the data is partially correct and partially false. False news detection also can be treated as a fine-grained multi-classification challenge by introducing multiple categories to data collections to tackle this limitation. The datasets supplied feature distinct Ground Truth Labels, and the regression construction gets difficult because translating the distinct labels to numerical scores appears to be a complex operation [1]. Every theory supplied its approach to the realization of opinion leader characterization. Consequently, we found the following shortcomings in earlier methodologies and highlighted our role in inducing them.

1) Used similar methods: In the above research articles, we have found that most of the research articles use the same method or model to eliminate some problems. Most of them are not using new technologies to get different solutions for the problem of getting the picture-related data people have used CNN or RNN to detect fake news, which is commonly used. However, we pursue the fundamental and straightforward process for the study. Both the supplied algorithms are precise and easy to grasp, and a new strategy to obtain the solution to the problem is delivering improved computational efficiency.
2) Absence of rumors tracking: The brighter side of the FND is to get track of rumors also, which are more dangerous as compared to fake news, but sadly, no intervention has made a genuine attempt in this area. Although several solutions focused on the user's attributes connected to social status, depth of understanding, half-truths, and certain types of fraudulent claims, in this study, we employed the MSVM, PCA, and firefly methodologies to get this issue out up to some level. We also employed trust, a vital aspect, for building a solid connection on the social media website.
3) Small datasets: Using proper datasets benefits the procedure's efficacy. As we have seen, most other options picked online blogs, a limited number of tweets and posts, and a small number of news items for their experiment, assessment, and results. Only a few methods used the real social network dataset for assessment reasons. We employed ten datasets for experimental analysis in this research. However, the suggested technique may be used for any dataset for assessment.
4) Limited solutions: Nowadays, a single answer is not always enough for dealing with all scenarios. Similarly, a single response is inadequate in identifying false news to determine the dataset's precise correctness and dependability. Recently, researchers provided a brief for the specific problem which is accruing most of the research articles faced which are getting half truth separated from complete lie, which is the most common problem we have faced some datasets are designed in that way so you can get half truth fake news truth news are rumor also in the data set.
5) Manipulated dataset: many articles use manipulated datasets according to their model's comfort to get more accuracy. Manipulated datasets are unreliable,

TABLE 1. Summarized review of literature papers.

Ref.	Methadology	Dataset	Advantages	Disadvantages
1-[2]	Text-CNN is utilized in the Similarity-Aware FakE news detection technique (SAFE), which enables it to analyze multi-modal (textual and visual) important data of media articles	PolitiFact GossipCop	Getting good performance on the visual-based datasets.	Not so much accurate on textbase datasets.
2-[12]	WELFake is a two-phase benchmark model for fake news detection that uses machine learning classification and is built on word embedding over linguistic data.	FakeNewsNet BUZZFEED	Give a better performance on the test base dataset as compared to above.	Used synthetic dataset not suitable for the visual dataset .
3-[13]	In UFNDA for feature extraction GRU(Bi-GRU) layer to detect fake news	weibo	Used for unsupervised fake news detection for text and media both.	Feature combination is very complex, and that makes its accuracy less.
4-[14]	Used two-phase learning, one is unsupervised learning for that SSL is purposed with CNN for supervised learning.	LIAR PHEME	Good performance on less labeled or semi-labeled datasets.	Accuracy is not that good.
5-[15]	One-ClassLearning (OCL) and Positive and UnlabeledLearning (PUL) are promising approaches for detecting content-based false news using a smaller number of labeled data than typical machine learning algorithms.	FakeNewsNet Fact-checked news	Semi-supervised ml algorithm and strategy used for unlabeled learning.	Accuracy is not that high as compared to other datasets.
6-[16]	BERT technique utilized for mutual learning framework that integrates relational characteristics classification (RFC) for named entity recognition (NER).	PolitiFact Pymedia	To simplify the problem, BERT is used.	Time complexity is very high than expected.
7-[17]	Fakenews detection technique based on Natural Language Inference (NLI) methodology with the aid of BERT is employed.	FakeNewsNet LIAR	Good for text-based datasets.	Not good for typical datasets like a liar.
8-[18]	Through ensemble approaches, CNN was utilized to combine stylometric characteristics and text-based word vector representations.	PolitiFact	The used assembled approach of deep learning makes it less complex.	Accuracy is good, but precision and recall are not good.
9-[19]	One-ClassLearning (OCL) and Positive and UnlabeledLearning (PUL) are promising approaches for detecting content-based false news using a smaller number of labeled data than typical machine learning algorithms.	PolitiFact	Used Bi-LSTM model for high performance.	Higher execution time for every epoch
10-[20]	Through ensemble approaches, CNN was utilized to combine stylometric data with text-based word vector representations.	PolitiFact Gossipcop	Deep learning is used to make algorithmic problems simpler	Accuracy is not up to the mark

TABLE 1. ***(Continued.)*** **Summarized review of literature papers.**

11-[21]	SVM two-layer consensus utilizing Byzantine fault-tolerant (BFT) and asynchronous tolerance widely accepted coin protocols.	Politifact	Better quality results	Accuracy can be increased ca be used MSVM
12-[22]	crawler and labeling module's features vector extraction by using a conspiracy classifier. BORJIS using NLP	FakeNewsNet	Better accuracy	Old algorithm tested on only one dataset
13-[23]	In ASSO-OSIW Salp Swarm Optimization (SSO), weight is employed for implementation based on a non-linear, significantly reduced rate of change and oscillating inertia.	ISOT LIAR Buzzfeed PolitiFact	Accuracy is more significant than most of the algorithms.	Accuracy is good, but precision and recall are not that good.
14-[24]	BERT tool designed for Arabic text	FakeNewsNet	Great accuracy	Old tech.
15-[25]	Multi Neural Network is used in the purposed method	PHEME Weibo	The purposed method makes the problem simple.	Accuracy is not that good.
16-[26]	a Bi-LSTM based (Bidirectional long short-term memory) deep learning strategy by putting self-attention on top.	FakeNewsNet	Accuracy is getting better in every epoch	Loss is also great
17-[27]	LSTM	FakeNewsNet	Accuracy is good.	Only tested on one dataset.
18-[28]	Applied multiple machine learning models for feature attraction.	FakeNewsNet	Make problems simple for feature attraction	Tested on only one dataset, so can not make it trustful.
19-[29]	CT-BERT and Roberta were applied to the COVID-19 false news dataset using the multiplicative fusion approach.	COVID-19 pandemic (2020)	Best accuracy for BERT algorithm in this table	Except for accuracy, precision and recall
20-[30]	Use of CNN with FT-MELMo embedding system	FakeNewsNet	Accuracy is good	Algorithm have high execution time
21-[31]	Flair library is used with DNN	ISOT	Time complexity is less	Accuracy is not that good.
22-[32]	To predict social networking behavior, a hybrid LSTM-SVM classifier is used.	COVID-19 pandemic (2020)	Accuracy is good	Not suitable for typical datasets like a liar.
23-[33]	Term Frequency–Inverse Document Frequency multi-level voting ensemble model.	FakeNewsNet	Accuracy is good	I tested on only one dataset, so I can not make it trustful.
24-[34]	several GCN, GAT, and GraphSAGE models are used	COVID-19 pandemic (2020)	Best accuracy on this dataset	Tested on only one dataset, so can not make it trustful.
25-[35]	Fake BERT is a deep learning approach based on BERT (Bidirectional Encoder Representations from Transformers), which mixes numerous parallel blocks of a single-layer deep (CNN) with varying kernel sizes and filters with the BERT.	FakeNewsNet	Best accuracy for BERT algorithm	Tested on only one dataset, so can not make it trustful .
26-[36]	A combination of deep neural network with optimal hyper-parameters.	PolitiFact FakeNewsNet Buzzfeed	Make problems simple for feature attraction	Not suitable for a typical dataset like a liar.

TABLE 1. *(Continued.)* **Summarized review of literature papers.**

27-[37]	An enfeeblement machine learning classifier (XGBoost) and a deep neural network model (DeepFakE)	Buzzfeed FakeNewsNet PolitiFact	Time complexity is less	Accuracy is not that good.
28-[38]	They have proposed CreditRank as an algorithm for assessing publications' social media reputations.	PolitiFact Gossipcop FakeNewsNet LIAR IFND	Performance is good for every dataset	Time complexity is more than expected.
29-[39]	a basic network design that combines the usage of contextual embedding like word embedding and leverages attention methods with pertinent metadata	LIAR	Time complexity is less	Accuracy is not good on the typical datasets.
30-[40]	Pre-trained encoders are used to create a content graph based on Edge-weighted Graph Attention.	PolitiFact Gossipcop FakeNewsNet LIAR	Accuracy is good on typical data set	Time complexity is more than expected.
31-[41]	MCNN-TFW, a various convolutional neural infrastructure false news detection	ISOT	Accuracy is good	Tested on only one dataset, so can not make it trustful.
32-[42]	Multi-network and CNN are used to increase the accuracy.	PHEME Weibo	Time complexity is less	Accuracy is not good on the typical datasets.
33-[43]	A semantic false news detection system based around relational characteristics like emotion, entities, or facts collected straight from the manuscript using NLP.	PolitiFact LIAR	Accuracy is good at typical datasets	This is not good for visual base dataset

and we cannot trust the synthetic dataset because this dataset is not official and does not pick a random ratio of fake and real news, so once you can achieve more accuracy on these kinds of models, they are not reliable.

III. FUNDAMENTAL OF FAKE NEWS DETECTION

In this section, we presented the explanation of fake news and fake news detection and the detailed information for the algorithms which are used in our purposed implementation, like detailed information for the machine learning model which is used in implementation with PCA and firefly algorithm

A. FAKE NEWS DETECTION SYSTEM

"News" denotes data relating to recent occurrences. This can be completed in several ways, with mouth word, publishing, postal services, transmitting, DC (digital communication), and the testimonies of incident participants and observers [62]. Fake news is the purposeful dissemination of erroneous data using conventional news outlets or social networking sites. An inaccurate statement travels quite quickly. FNs (fake news) has become one of the main impediments in our digitally linked society. Fake news travels at incredible speeds, affecting vast numbers of people per day through enticement and trigrams. As a result, detecting FN has become a critical problem that has sparked intense studies. Detecting FN on social media is a new difficulty every time. It was shared on social media to deceive users [63]. FNs spread faster on Facebook during the 2016 Presidential campaign in the US than in real news. Detecting fake news on social media has piqued the interest of politicians and academics alike. Fake news identification on social networking sites is critical. This is due to fake news potentially affecting people's thoughts, societies, and countries.

B. CATEGORIES OF FN (FAKE NEWS)

The several categories of FNs are discussed below: • User-based: Fake accounts create this form of fake news that is focused on a specific population, which may include people of a given age, religion, language, or political affinity. • Visual based: Graphics, such as manipulated graphics, digitally altered videos, or a fusion of both, is used more for these false media articles as material. • Stance-based: It presents factual statements so that their context and intention are altered. • Knowledge-based: Such posts provide comprehensive (so-called) explanations for unaddressed situations, leading individuals to assume the information is genuine—for instance, natural therapies for high blood sugar levels in humans [64].

C. IMPACT OF FN

However, on SM (social media) sites, the range and consequences of sharing data are strongly impacted and happen at quite a rapid rate that skewed, erroneous, or fraudulent data has an enormous opportunity to have real-world implications for millions of subscribers within moments. Users' ability to differentiate what is fake or what is true when browsing and actively participating in information-overloaded platforms has become a social issue [65].

D. MSVM FOR FAKE NEWS DETECTION

SVMs were created with binary classification issues in mind. When working with many classes, however, a multi-class method is required. Because two-class or binary classification issues are significantly simpler to answer, various strategies for extending it to multi-class problems have been offered. In this piece, one class is pitted against the others. A method that compares one class to all others compares one class to all others. It essentially creates L (in this case, $L = 8$) hyperplanes, each isolating one class from the others. As a result, L decision functions are generated, and an observation X is assigned to the class with the most excellent decision function. The following material is appropriate for discussing the fundamentals of binary SVM. The Support Vector Machine (SVM) has been proven to offer decent classification results on several occasions [67]. By concentrating on the training instances near the edge of the class descriptors, the SVM approach aims to uncover the suboptimal disconnection hyperplane between classes. SVMs are a kind of training scenario. This strategy not only fits an ideal hyperplane but also utilizes significantly fewer training samples, resulting in slightly elevated classification accuracy with limited training sets. Consider a supervised binary classification issue to illustrate the fundamental concepts of SVM.

E. PCA FOR FAKE NEWS DETECTION

Principal Component Analysis Feature Extraction works on the criteria of extracting the Principal Components(PCs) along with maximizing the variance of the data. The covariance matrix of the data is used to obtain the PCs by solving its eigenvalue problem. The largest eigenvalue is the first PC followed by the next PC. Most of the times, the distribution of PCs among the Variances are not uniform but is more towards the larger eigenvalues. Thus, very small number of PCs are enough to capture most of the variances. The input dimension is reduced by finding the PCs with the transformation of project data into it. There are three main steps for this method - Augmentnation of class information to data, followed by feature extraction by PCA and determining the transformation matrix.

F. FIREFLY RELATED TO FAKE NEWS DETECTION

Fireflies (Coleoptera: Lampyridae) are among the fascinating insects, inspiring poets and scientists with their magnificent courting displays [69]. There are now about 2000 species on the planet. Fireflies dwell in various heated habitats and are most active at night throughout the summer. Many scholars have investigated firefly phenomena in nature, and there are countless studies on the subject [70], [71]. The flashing light generated by the biological process of bioluminescence distinguishes fireflies (fig.4). The critical courting cues for mating might be flashing lights. The flashing light may serve as a warning to prospective predators and enticing mating partners. It is worth noting that certain mature firefly species lack bioluminescence. Similar to ants, these animals use pheromones to attract mates. Bioluminescent processes take occur in fireflies' lanterns, which produce light. Only slowly modulated flashes are produced by most bioluminescent species (also glows).

On the other hand, adults of many firefly species can regulate their bioluminescence to produce intense and distinct flashes. Impulses start the light-production of the lanterns from the firefly's central nervous system. The majority of firefly species use bioluminescent courting cues. Flying males are usually the initial signalers, attempting to attract flightless females on the ground. Females generate continuous or flashing lights in response to these cues. Both mating partners generate distinct flash through a process called that are timed to send encrypted messages such as species identity and sex. The partnering signal attracts females, considering the differences mentioned above. Females typically prefer male pyrotechnics that are brighter. The flash power is commonly recognized to vary the increasing distance from the center. Fortunately, females of some firefly species cannot discern between distant flashes from more robust light sources and adjacent flashes caused by poorer light sources. Since firefly flash nerve impulses are exceedingly visible, they may deter an extensive range of probable predators. Flash signals originate as protective mechanisms to alarm people about the dangers in the sense of evolutionary processes [72], in which only the single most essential individuals survive. Particle swarm optimization has two aspects: consciousness and decentralized decision-making. Bees in hives, ants in holes in the ground, and other autonomous creatures live together in the same shared space. It is required for organization members and other people together to communicate directly or exchange information in good enough conditions to live in harmony (sociality) (sociality). Individuals within a group cannot work as if they are alone and, therefore, must instead make adjustments to the organization's operational aims [73].

IV. PROPOSED METHODOLOGY

The existing fake news detection methods suffer from limited datasets and high computational costs. A fake news classification model task to determine whether a small amount of information is correct or incorrect is the fundamental instance of misinformation identification. However, the binary classifier approach is inadequate when the data is partially correct and partially false. False news detection also can be treated as a fine-grained multi-classification challenge by introducing multiple categories to data collections to tackle this limitation. The datasets supplied feature distinct Ground Truth Labels, and the regression construction gets difficult because translating the distinct labels to numerical scores appears to be a complex operation [1]. Therefore, there is a need for a methodology to overcome the existing issues

A. METHODOLOGY

The proposed system utilizes a novel database to create a decision model based on the MSVM classification technique. The proposed model will be used to classify or detect the news as fake or real.

B. DATA GATHERING AND PRE-PROCESSING

Generally, it will collect reviews or comments from different sections, fake or real. Most researchers can gather the data from online sites. After the gathering phase, it will upload the input comment data and verify the feasibility of the news dataset when the dataset will explore. Before classifying the comments and reviews, the following steps are applied to datasets: • Data cleaning • Stemming.

C. FEATURE EXTRACTION USING PCA METHOD

In this proposed work, PCA will be used for feature extraction from images. The principal component analysis reduces the dimension of the data set comprising many related variables and recalls the maximum change in actual data. The principal component analysis simplifies the information by converting the linear data and generating novel coordinates with significant variations [74]. It is the multi-variant numerical instrument used to estimate multiple-dimension data. It is used in every research area to manipulate many variables. It is attained by changing the actual variable set into a small number of the variable. Thus, a novel variable is related to grouping the actual variables. The principal components are organized where small components are available in the current variables.

D. FEATURE SELECTION USING FIREFLY (FA) OPTIMIZATION METHOD

Metaheuristic methods are basically divided into nine different optimization methods. These methods include Physics Based, swarm based, social based, music based etc [80] and [81]. This proposed work will select the essential features with a firefly-optimized algorithm. This algorithm is classified as swarm intelligent Metaheuristic method [83]. The FA is one of the various evolutionary algorithms (EAs) with various purposes. It is suitable and straightforward measures and efficacy, inspection, and analysis throughout numerous disciplines. Several experiments have been conducted to improve the standardized firefly algorithm's competence and adapt it to the nature of the problem. Yang devised this approach based on the theoretical framework that specific bugs are unisexual and that almost all flies have the appealing capability for one another. Still, that desirability is approximately equal to particular light conditions [75]. As a result, the brightest firefly encourages less bright ones to travel forward; however, if no flies are brighter than a particular firefly, it will migrate at irregular intervals. The objective function of the firefly algorithm is linked to the population's strobe light [82].

Algorithm 1 PCA Feature Extraction

Require: $PreprocessDataMatrix$
  $[row, col] = size(input\_value)$
  $M = mean(input\_value)$
  $D = input\_value - repeat(M, 1, col)$
  $co = D * D'$ {Construct the covariance_matrix}
  $[V, E] = eig(co)$ {Eigen Values}
  $E = diag(E)$ {Construct a diagnol matrix}
  $[R, C] = sort(-E)$ {sorting}
  $E = E(C)$
  $V = V(:, C)$
  $C = 0$
  for i=1:size(E,1) **do**
    if E(i)>1 **then**
      $C = C + 1$
    end if
  end for
  DD=V(:,1:C)
  $Extracted\_Feature = DD' * D$
  Fin

Algorithm 2 Selection Process: Firefly

Require: $max\_iteration, a, b, y, InitialPopulation$
  {Determining intensity at cost for each individual}
  while T<iter_max **do**
    for I=1:m **do**
      for j=1:m **do**
        if Ij>Ii **then**
          Move firefly I towards j in K-dim
        end if
        Calculate new_solutions and update light intensity
      end for
    end for
    Rank the fireflies and search the current_best
  end while
  FIN

E. MSVM CLASSIFICATION METHOD

For the classification of fake news, an MSVM classifier algorithm will be implemented. MSVM is a supervised learning-based machine learning technique that aids in classification and regression. MSVM's primary goal is to build different class clusters and hyperplanes. Multi- SVM is the simplest way to classify multiple classes of data.

MSVM shows modern achievements in real-life programs like picture categorization, biometrics, hand-written character discovery, etc. If multiple class categorization issues occur, such a problem appears complicated as the outcomes can be numerous and might be split into N collective types.

There exist various methods for resolving multiple class categorization issues for SVM. The two main methods are the One-Vs-One classifier as well as One-Vs-All classifier. The basis of this survey is the One-Vs-All classifier. Every class is divided, and another type is also grouped for selecting the group that categorizes the test information having the most significant margin [76]

Algorithm 3 Featured-Optimized-MSVM Classifier

Require: $F[0:n-1]$ {A feature set with n features, sorted information gain}
  $Low = 0$
  $High = n-1$
  $Val = acc(n-1)$
  $I\_msvm(f[0..n-1], val, L, H)$
  if H<=L **then**
    return $f[0..n-1]andval$
  end if
  $Mid = (L+H)/n$
  $Val\_1 = acc(Mid)$
  if val_1>=val **then**
    return $if\_MSVM(f[0,..Mid], value\_1, L, Mid)$
  else if val_1<val **then**
    return $if\_MSVM(f[0..H], val, Mid, H)$
  end if

F. EXTRACT THE FEATURES, SELECT THE FEATURES, AND CLASSIFY

As we can see in fig. no (2), the proposed model will move forward to the next feature extraction phase (FE) after the data pre-processing step. It will extract the features and reliable optimized feature sets with the help of the FE approach using optimized PCA. The extracted feature set data is then processed with the feature optimization procedure. Here, the optimized PCA and FA (firefly Optimization) algorithm occur. This phase processes the dataset gives the optimized feature sets for classification models, and optimizes exceptions. The optimization procedure is only used to enhance the classification accuracy, error rate, etc. This FE model extracts each component from a dataset. It should calculate only several eigenvalues and vectors. It is more calculation and practical to extract the feature sets. The labels or groups are the names of reviews or comments where the feature sets take place. The training set will use to classify the result for the testing module. Then, it gets saved inside the recent execution directory of the research model. Usually, the best result achieved during optimization is calculated as the fitness solution to the problem search by the proposed model, known as an optimized, feature-based FA with the MSVM model. This proposed model has automatically studied the important feature vectors without human interaction. This proposed model attains the benefits of providing maximum performance. At the last of the proposed model, various performance metrics are evaluated and compared with the existing techniques to search for enhancements in the proposed method.

V. EXPERIMENTAL RESULTS

We have used ten datasets for applying the proposed algorithm: PolitiFact, Gossipcop, Twitter's Election Integrity, FakeNewsNet, Buzzfeed, Weibo, Liar, PHEME, ISOT, and COVID-19 pandemic (2020). We used Python 3.0 on an Intel i5 9th-generation processor with 8 GB RAM and GPU NVIDIA GTX 1650 4GB to obtain the experimental results. The proposed algorithm was applied to all the mentioned datasets under the same training and testing conditions for proper comparision.

A. DATASET

We utilized the ten genuine datasets as mentioned in table 2: PolitiFact, Gossipcop, Twitter's Election Integrity, FakeNewsNet, Buzzfeed, Weibo, Liar, PHEME, ISOT, and COVID-19 pandemic (2020). The structure of the datasets is explained in this subsection.

1) PolitiFact DATASET

The news stories in the datasets are all taken from PolitiFact. PolitiFact (https://www.politifact.com/) is a well-known non-profit in the United States that fact-checks political claims and reports.

2) GossipCop

GossipCop is used to gather news stories for the datasets. GossipCop (https://www.gossipcop.com/) fact-checks celebrity reports and entertainment articles in magazines and newspapers. PolitiFact news items were released between May 2002 and July 2018, whereas GossipCop news pieces were produced between July 2000 and December 2018 [53].

3) TWITTER's ELECTION INTEGRITY

The initial misinformation dataset comes from Twitter's Voter Suppression Hub4, where three layers of false news were uncovered in the Late summer of 2019. This dataset features a total of 13,856,454 posts on Twitter and contains 31 variables that show tweet-related facts about not only the tweet's content and the person [54].

4) FakeNewsNet

FakeNewsNet consists of only 422 news articles with incomplete classification in real and fake categories [55].

5) BuzzFeed

BuzzFeed News is a data set with less number of news datasets containing 101 news it is used to check the system on a shorter datasets [56].

6) WEIBO

WEIBO dataset [57] was gathered from Xinhua News Agency1 and Weibo.2 The former is a reliable news source,

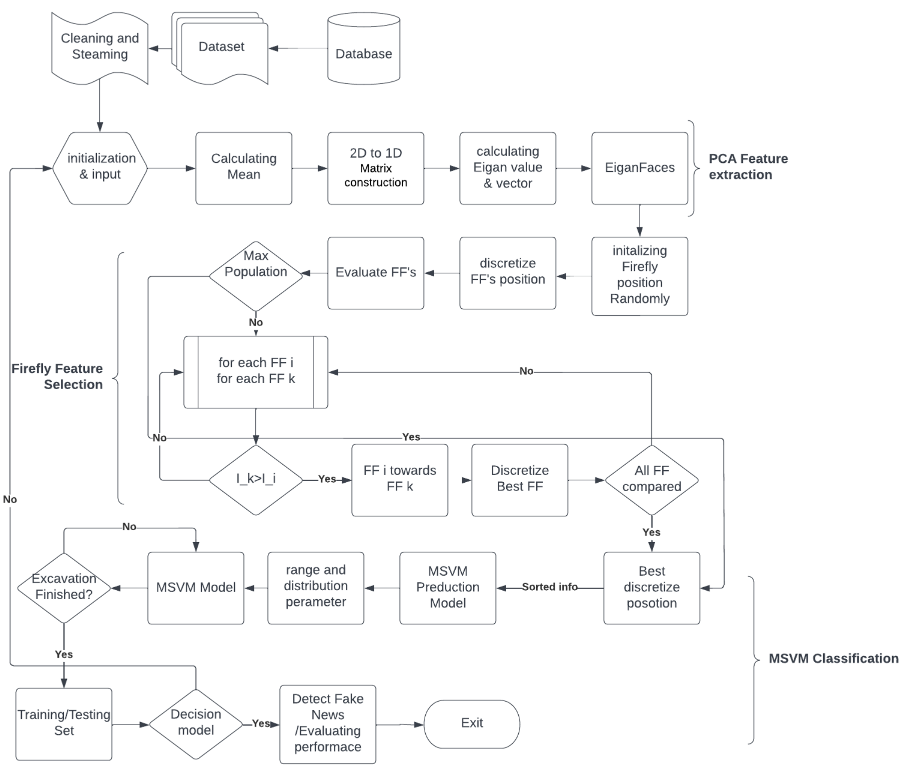

FIGURE 2. Proposed Model's Flowchart.

TABLE 2. Dataset Information.

Ref.	Dataset	Fake News	Real News	Total News
1-[52]	PolitiFact	432	624	1056
2-[53]	Gossipcop	5323	16817	22I40
3-[55]	Twitter's Election Integrity	6,235,123	7,621,331	13,856,454
4-[56]	FakeNewsNet	211	211	422
5-[57]	Buzzfeed	45	56	101
6- [9]	Weibo	4749	4779	9528
7-[58]	LIAR	5500	7300	12800
8-[59]	PHEME	27,992	64,507	92,499
9-[60]	ISOT	23,481	21,417	44,848
10-[61]	COVID-19 Pandemic (2020)	3060	3360	6420

whereas Chinese microblogging platform. The information was gathered between May 2012 and January 2016. There are 9528 posts in all, including 4749 fraudulent posts, 4779 true posts, and 9528 photos relating to postings in the dataset. Each post in the WEIBO dataset includes text and a unique picture. Xinhua News Agency verifies if the posts in the dataset are fraudulent or true news.

7) LIAR

LIAR comprises different hard-to-classify social media postings and speeches owing to the absence of verification process sources or knowledge bases [9].

8) PHEME

The PHEME dataset [58] includes of data based on five breaking stories, encompassing charliehebdo, Robertson, the German wings crash, the Ottawa shooting, and the Sydney siege. Each news contains a series of postings, containing a substantial quantity of prose and graphics correlating to that same tweets with labels.

9) ISOT

There are two categories of news in ISOT data: genuine and bogus. There are 44,848 news pieces in the data collection, including 21,417 true news and 23,481 fraudulent news [59].

10) COVID-19 PANDEMIC (2020)

The COVID-19 false news English dataset [60] was given with the id, tweet, and label ("Fake" and "Real") in the form of TVs during the COVID-19 epidemic (2020).

B. ANALYSIS AND VISUALIZATION OF THE EXPERIMENTAL RESULT

This subsection discusses the results of the proposed algorithm on all above mentioned datasets. Now, we deployed the proposed algorithm on the all ten datasets in which we have compared accuracy with the other models which are using the same datasets. Further, to support the effectiveness of the suggested algorithm, we compared the experimental findings with the Fake News diagnosis parameters results in terms of accuracy, precision, recall, and F1-score [22].

1) ACCURACY TEST ON PolitiFact DATASET

In the given fig.(5), We are comparing purposed model with the other models which are claiming accuracy on this similar dataset.

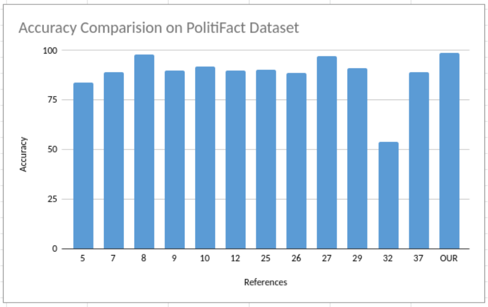

FIGURE 3. Accuracy comparison on PolitiFact dataset.

TABLE 3. Accuracy Comparison on Politifact dataset.

Reference	Accuracy
[5]	84%
[7]	89%
[8]	97.8%
[9]	90%
[10]	92%
[12]	90%
[25]	90.4%
[26]	88.6%
[27]	97%
[29]	91%
[32]	54%
[37]	89%
Our Proposed Algorithm	**98.7%**

As we can see in fig.(5), that our purposed model is outperforming every model and it has 98.7% accuracy almost 1% higher accuracy than the highest accuracy claim by the best algorithm which is 97.8% in this dataset [19]. Our model is more consistent in every epoch which we run while testing it on this dataset.

2) ACCURACY TEST ON FakeNewsNet DATASET

In the given fig.(6), We are comparing purposed model with the other models which are claiming accuracy on this similar dataset.

As we can see in fig.(6), our proposed model outperforms every model, and it has 99.64% accuracy, almost .7% higher than the best algorithm's highest accuracy claimed 98.90% in this dataset [35]. Our model is more consistent in every epoch we run while testing it on this dataset.

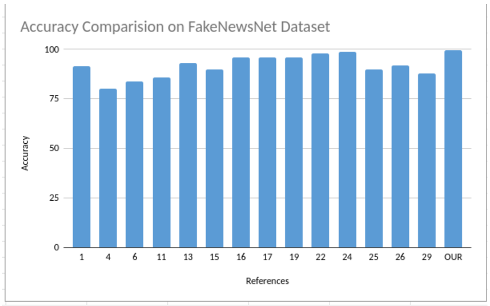

FIGURE 4. Accuracy comparison on FakeNewsNet dataset.

TABLE 4. Accuracy Comparison on FakeNewsNet dataset.

Reference	Accuracy
[1]	91.6%
[4]	80%
[6]	84%
[11]	86%
[13]	93%
[15]	90%
[16]	96%
[17]	96%
[19]	96%
[22]	98%
[24]	98.9%
[25]	90%
[26]	92%
[29]	88%
Our Proposed Algorithm	**99.64%**

3) ACCURACY TEST ON BuzzFeed DATASET

In the given fig. (7), We are comparing the purposed model with the other models claiming accuracy on this similar dataset.

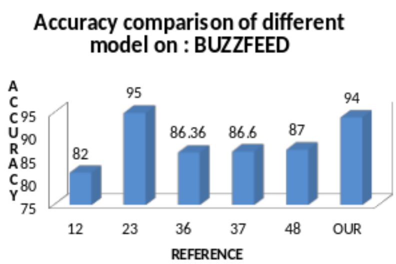

FIGURE 5. Accuracy comparison on BuzzFeed dataset.

TABLE 5. Accuracy Comparison on Buzzfeed dataset.

Reference	Accuracy
[12]	82%
[23]	95%
[36]	83.6%
[37]	86.6%
[48]	87%
Our Proposed Algorithm	**94%**

As we can see in fig.(7), our proposed model is underperforming the best model and has 94% accuracy, almost .7%

lesser accuracy than the highest accuracy claim by the best algorithm, which is 95% in this dataset [23]. Our model is more consistent in every epoch we run while testing it on this dataset, but it cannot best the accuracy in this dataset compared to the existing model, which we can improve in feature.

4) ACCURACY TEST ON WEIBO DATASET

In the given fig. (8), We are comparing the purposed model with the other models claiming accuracy on this similar dataset.

TABLE 6. Accuracy Comparison on Weibo dataset.

Reference	Accuracy
[13]	81.6%
[25]	86%
[42]	87%
[44]	93.8%
[45]	93.7%
[49]	94%
Our Proposed Algorithm	**94.7%**

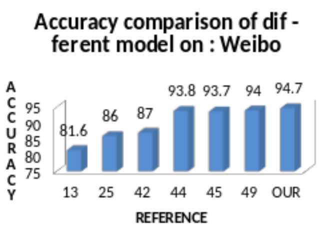

FIGURE 6. Accuracy comparison on Wiebo dataset.

As we can see in fig.(8), our proposed model outperforms every model, and it has 94.74% accuracy, almost 0.9% higher than the highest accuracy claimed by the best algorithm, which is 93.80% in this dataset [44]. Our model is more consistent in every epoch we run while testing it on this dataset.

5) ACCURACY TEST ON LIAR DATASET

In the given fig (9). We are comparing the proposed model with the other models claiming accuracy on this similar dataset.

As we can see in fig.(9), our proposed model outperforms every model, and it has 65% accuracy, almost .7% higher than

TABLE 7. Accuracy Comparison on LIAR dataset.

Reference	Accuracy
[14]	58%
[17]	38%
[23]	41%
[38]	33%
[39]	46%
[40]	60%
[43]	64.3%
[47]	61%
Our Proposed Algorithm	**65%**

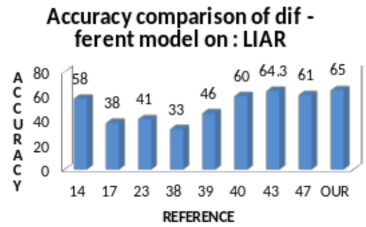

FIGURE 7. Accuracy comparison on LIAR dataset.

the highest accuracy claimed by the best algorithm, which is 64.30% in this dataset [43]. Our model is more consistent in every epoch we run while testing it on this dataset.

6) ACCURACY TEST ON PHEME DATASET

In the given fig. (10), we compare the proposed model with the other models claiming accuracy on this similar dataset.

TABLE 8. Accuracy Comparison on PHEME dataset.

Reference	Accuracy
[14]	59%
[25]	85%
[40]	62%
[42]	88%
[45]	84.8%
[49]	86%
Our Proposed Algorithm	**88%**

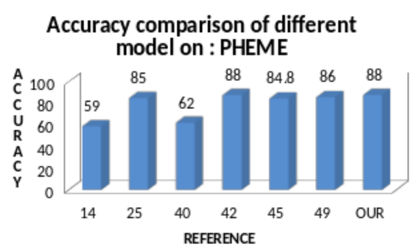

FIGURE 8. Accuracy comparison on PHEME dataset.

As we can see in fig. (10), our proposed model outperforms every model, and it has 88% accuracy, almost the same accuracy as the highest accuracy claimed by the best algorithm, which is 88% in this dataset [42]. Our model is more consistent in every epoch we run while testing it on this dataset. We are only able to achieve the much accuracy which is claimed by the existing method. In the future, we will try to make it better.

7) PERFORMANCE TEST ON GossipCop DATASET

In the given fig. (11), We are comparing the proposed model with the other models claiming their performance parameters like Precision, Recall, Accuracy, and F1-score on this similar dataset.

TABLE 9. Performance Comparison on GossipCop dataset.

Reference	Precision	Recall	Accuracy	F-1 Score
[2]	85.7%	93.7%	83.8%	89.5%
[20]	87%	81%	92%	84%
[38]	98.5%	96.6%	98.9%	97.5%
[40]			86%	86.6%
Our	97.8%	96%	97.7%	96.3%

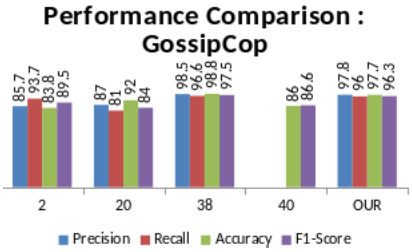

FIGURE 9. Performance comparison: GossipCop.

As we can see in fig.(11) that, our proposed model is underperforming for one model, and it has 97.7% accuracy, 97.8% precision, 96% recall, 96.3% F1-Score almost 1.1% lesser accuracy than the highest accuracy claim by the best algorithm which is 98.8% accuracy, 98.5% precision, 96.6% recall, 97.5% F1-Score in this dataset [38]. Our model is more consistent in every epoch we run while testing it on this dataset, but it cannot get the best accuracy compared to the existing model, which we can improve in features.

8) PERFORMANCE TEST ON TWITTER ELECTION INTEGRITY DATASET

In the given fig. (12), We are comparing the proposed model with the other models claiming their performance parameters like Precision, Recall, Accuracy, and F1-score on this similar dataset.

TABLE 10. Performance Comparison on Twitter Election Inegrity dataset.

Reference	Precision	Recall	Accuracy	F-1 Score
[50]	98.5%	98.1%	48%	98.2%
[51]	93.6%	91.3%	91.4%	92.1%
[52]	92.6%	91.4%	92.8%	92.7%
Our	98.5%	98%	98%	98.4%

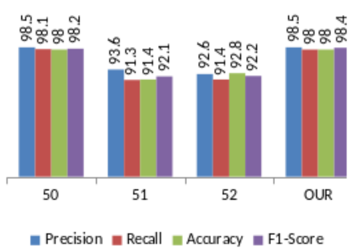

FIGURE 10. Performance comparison: Twitter Election Integrity.

As we can see in fig.(12) that our proposed model is performing equal to the best model, and it has 98% accuracy, 98.5% precision, 98% recall, 98.4% F1-Score, which has almost equal accuracy to the highest accuracy claimed by the best algorithm which is 98% accuracy, 98.5% precision, 98.1% recall, 98.2% F1-Score in this dataset [50]. Our model is more consistent in every epoch we run while testing it on this dataset, but it cannot get the best accuracy compared to the existing model, which we can improve in features.

9) PERFORMANCE TEST ON ISOT DATASET

In the given fig. (13), We are comparing the proposed model with the other models claiming their performance parameters like Precision, Recall, Accuracy, and F1-score on this similar dataset.

TABLE 11. Performance Comparison on ISOT dataset.

Reference	Precision	Recall	Accuracy	F-1 Score
[23]	100%	89.3%	94.5%	94.5%
[31]	91.3%	98.5%	95.04%	94.8%
[41]	98.7%	96.7%	97%	96.8%
[47]	99%	99.1%	99%	98.9%
Our	99.1%	99.5%	99.6%	99.6%

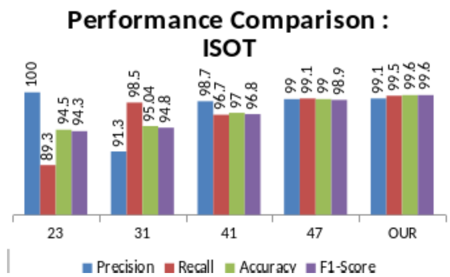

FIGURE 11. Performance comparison: ISOT.

As we can see in fig.(13) that our proposed model outperforms as compared to the best model, and it has 99.5% accuracy, 99.1% precision, 99.5% recall, 99.6% F1-Score, which has more accuracy than the highest accuracy claim by the best algorithm which is 99% accuracy, 99% precision, 99.1% recall, 98.9% F1-Score in this dataset [47].

10) PERFORMANCE TEST ON COVID19 DATASET

TABLE 12. Performance Comparison on COVID-19 dataset.

Reference	Precision	Recall	Accuracy	F-1 Score
[29]	99.1%	98.7%	98%	98.6%
[32]	98%	98%	40%	96%
[34]	91.8%	97%	93%	92.9%
[46]	91.96%	93.63%	94.15%	92.61%
Our	99.2%	99%	94.8%	98.5%

In the given table 12, the proposed method with feature selection techniques gave a better performance compared to other algorithms.

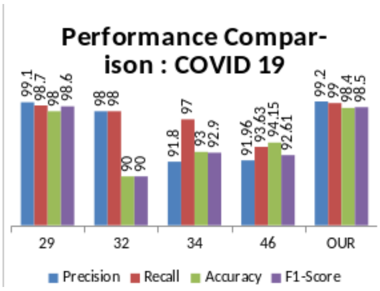

FIGURE 12. Performance comparison: COVID19.

As we can see in fig.(14) that our proposed model outperforms as compared to the best model, and it has 98.4% accuracy, 99.2% precision, 99% recall, 98.5% F1-Score, which has more accuracy than the highest accuracy claim by the best algorithm which is 98% accuracy, 99.1% precision, 98.7% recall, 98.6% F1-Score in this dataset [29].

VI. CONCLUSION AND FUTURE SCOPE

Even though there are various benefits of social media, fake news reduces it's quality. Manually detecting fake news is a time consuming task. In this paper, we have addressed an MSVM-based approach for detecting fake news. We have also used a different model for feature selection and feature extraction to improve the model on different types of datasets. For feature extraction, we used the optimized two-phase PCA called TP-PCA. We also proposed a Firefly based feature extraction method for the Multi-Class Support Vector Machine. The proposed algorithm was tested on ten different datasets including FakeNewsNet, LIAR, ISOT, PolitiFact etc. As the datasets had many features, applying feature selection methods gave a better performance compared to the methods in which all the features were used in training of deep learning models. Only the datasets having less number of features gave a lower performance on our feature extraction algorithms. In the Future, we plan to use deep learning models tuned with optimized machine learning multi-model to achieve better accuracy. We also plan to use these feature selection and feature extraction approaches in image and video based data to detect fake news using Recurrent Neural Networks.

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