International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-2, December 2019

Reinforcement based Multi-Model Deep Learning Algorithm for Classification

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Abstract*: Nowadays researchers are focused on processing the multi-media data for classifying the queries of end users by using search engines. The hybrid combination of a powerful classifier and deep feature extractor are used to develop a robust model, which is performed in a high dimensional space. In this research, a three different types of algorithms are combined to attain a stochastic belief space policy, where these algorithms include generative adversary modelling, maximum entropy Reinforcement Learning (RL) and belief space planning which leads to develop a multi-model classification algorithm. In the simulation framework, different adversarial behaviours are used to minimize the agent's action predictability, which has resulted the proposed method to attain robustness, while comparing with unmodelled adversarial strategies. The proposed reinforcement based Deep Learning (DL) algorithm can be used as multi-model classification purpose. The single neural network algorithm can perform the classification on text data and image data. The RL learns the appropriate belief space policy from the feature extracted information of the text and image data, the belief space policy is generated based on the maximum entropy computation.

Index Terms*: Deep Learning Algorithm, Document Classification, Image Classification, Multi-Model Classification, Reinforcement learning.

I. INTRODUCTION

Nowadays, multi-media such as audio, image, graphics, text and video are available on internet, which leads to the problem of analysing the multi-modal. However, new challenges are raised due to difference in semantic gap and various modalities. The human-brain mechanism is simulated to process multi-modal data by developing the computational models in prior works [1]. At present, various data are collected from the users, which are stored in the digital format. These data are easily available to public because of explosive growth of internet, which leads to a huge amount of multi-media data in different types namely video, audio, text, images, etc [2]. In this subject, the existing analysis problems are characterized by using high dimension and massive size features in multi-media data [3] [4].

Revised Manuscript Received on December 30, 2019.
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The one of the major problems need to solve is the development of artificial intelligent systems to deal with the massive data effectively [5]. In addition, the diversity and complexity of those datasets along with dimensionality and quantity are increasing in recent times. The previous studies faced the challenges like incompetency and were computationally inapplicable to model and analyse the multi-media data [6]. The system and time requirements are increased by high dimensionality problem and also provides poor performance in classification task [7]. The degradation occurred for differentiating the pairwise distance between points due to increase in the number of features i.e. dimensionality. Therefore, the inaccurate or wrong results are provided by various approaches [8]. In the community of data science, the major challenges are the classification and categorization with complex data namely video, documents and images. Researchers developing the various models using DL architectures and structures to solve these problems. But, these architectures are majorly designed for a particular domain or types of data. Across a wide range of data types for classification and categorization, the general information processing methods should be designed [9].

In real-world applications namely games, arts, science and autonomous vehicles, deep neural networks are developed and directly used, because it is considered as one of the major algorithms in machine learning [10]. When compared to challenges presents in multimodal learning, many of these studies overcomes the issues of single modal DL. Even though, there are missing values or errors presents in one or few modalities, an effective multimodal systems significantly improved the retrieval and final detection performance using various data types. By this way, the detection of events not only from videos, but also from audio and text are carried out by human brain. The audio can be obtained by listening process as well as the text are obtained by reading its description.

In this paper, the stochastic belief space policy is obtained by presenting the multi-model classification algorithm, which is developed by combining generative adversary modelling, maximum entropy RL and belief space planning. In the first step, different types of datasets, such as text and images are used to extract the important features for classification. The features are given to the proposed RL for classification. A complicated mixture of behaviours are represented by learning a policy from the simulator of black-box in a planning-based approaches, but it is a difficult process in RL algorithms. The predictability of the actions is minimized by reducing the resultant policy of exploitability using the maximum entropy framework. The reinforcement algorithm trained based on soft Q learning.

The remaining paper consists of: Section II presents a broad survey of recent papers in multi-model classification methodologies. The proposed methodology is described in section III. In section IV, performance of the proposed multi-model DL algorithm is described. The conclusion is made in section V.

II. RELATED WORKS

The processes of various modalities consists of audio, visual and text signals by using multimodal DL is a challenging process, because it is difficult to integrate the heterogeneous data in a common architecture. In this section, descriptions of the recent multi-model methodologies are presented.

Kim, Edward, and Kathleen F [11] classified the intention category from the information graphics, this study presented the multimodal DL approaches in a single neural network. The extraction of two modalities were carried out from the information graphics, where raw pixel data was the first modality. The dimension of feature vector was obtained by using four pooling or convolution layers of multimodal DL approach. In the information graphics, the usage of text represented by the second modality. The features of text were extracted from all the training and testing images, the author utilized the latest version of Tesseract.

Tian, Haiman, et al. [12] used videos for event detection by using a multi-modal DL framework in deep neural networks. At first, many useful information were extracted from different modalities by using various DL approaches. To extract the features from the visual and audio input, Convolutional Neural Networks (CNN) were used, where the text features were obtained by using word embedding. The two different data representations were described by this framework such as video level and frame-level. While comparing with existing conventional fusion techniques, the proposed approach gained higher effectiveness, which was proven by experimental results. The accuracy was improved by nearly 7% to 16% from a single modality and fusion techniques.

Jiang, Yu-Gang, *et al.* [13] integrated the useful clues by presenting the novel hybrid DL techniques, where those clues were obtained from different modalities namely motion patterns, information for spatial, audio and temporal dynamics. The corresponding features were extracted by using CNN, which operated on audio, motion and appearance signals. The relationships among features were captured by employing the feature fusion network and then derived the unified representation. Among video semantics, leveraging contextual relationships presented the refined prediction scores. The experiments were conducted on two benchmark datasets, such as Columbia consumer videos and UCF-101 dataset. This proved that the CNN approach achieved 84.5% and 93.1% classification accuracy on consumer dataset and UCF-101 while comparing with other techniques.

Kowsari, Kamran, *et al* [14] found the best DL architecture for classification by implementing the Random Multi-model DL (RMDL). These approaches were used to improve the accuracy and robustness and to classify the data, those approaches uses the various types of input namely, video, text, symbolic and images. The experiments were conducted on several publicly available datasets, which showed that the RMDL approach provided better performance on all datasets against existing techniques.

Heidarysafa, Mojtaba, *et al* [15] classify the data by developing the RMDL approach, which was a combination of DL and ensemble approach. The accuracy and robustness were improved by finding the best DL architecture through ensemble techniques of RMDL. The better results were achieved by training the multiple random models such as CNN, deep neural network and Recurrent Neural Network (RNN). The experimental results were carried out by using the datasets such as CIFAR-10 datasets and MNIST for classifying the images and then, IMDB, Reuters, 20NewsGroup and WOS datasets were used for classifying the texts. In addition to this, a face recognition task was carried out using ORL dataset.

III. PROPOSED METHODOLOGY

The research work implemented the multi-model classification algorithm to achieve the stochastic belief space policy by developing the combined algorithms such as generative adversary modelling, maximum entropy RL and belief space planning. Initially, the features are extracted from multiple types of datasets such as text and images. Those features are given to the proposed RL for training purpose. In the following sub-section, the process of extracting the features are described.

A. Pre-processing and Feature Extraction

1) Text and Sequences Feature Extraction

Generally, the features from the text files are extracted by using various natural language processing based techniques such as word embedding, TF-IDF etc. Specifically, in this research, word vectorization techniques and N-gram representation are utilized as feature extraction methodology for obtaining the features from the text files. From each text file, based on the glove word embedding methodology, the vector space models, which is a mathematical mapping of word space are generated with the help of the following Eq. (1).

$$d_j = \left(w_{1,j}, w_{2,j}, ...w_{i,j}, ..., \mathrm{w}_{l_j,j}\right) \tag{1}$$

Where, document length is illustrated as l_j and GloVe word embedding vectorization is described as $w_{i,j}$.

2) Image and 3D Object Feature Extraction

Feature extraction is a major factor in the image classification process, in this research, the images are either grey scale image or colour image. For the grey scale image such as MNIST dataset, the features are represented in the form of $h \times w$ and the features of the colour images are represented as $h \times w \times c$ where input image's height is depicted as h, image's width is described as w, and finally the RGB based 3 dimension colours is denoted by c.

The feature representation of the 3D objects is represented based on the n number of cloud points, the each cloud point consist of six set of features such as (x,y,z,R,G,B). Since a 3D object varies with the other 3D objects, due to the number of cloud points, which makes the 3D objects to be represented in an unstructured form. The unstructured 3D objects can be represented in the form of a structured format with the help of a simple instance up/down sampling technique.

B. Proposed methodology

The active perception problem is a planning problem, defined by the tuple $(S,A^a,A^o,T,O,R,b_o,\gamma)$, where state of the word is described as $S=(S^o,S^p)$, which consists of S^o as set of observable states and S^p is represented as the set of partially observable states. Then, an autonomous agent's action is described as A^a and finally, the action of opponents are denoted by A^o. Once the action is unique, then an intention can be easily identified, where the type of intention is observed based on those actions. The transition probability is represented by $T:S\times A^a\times A^o\rightarrow\Delta_S$, where space of the probability distribution is given as Δ, the probability for observation is illustrated as $O:S\times A^a\rightarrow\Delta_{A^a}$. The reward function is presented as $R:S\times A^a\times A^o\rightarrow\mathbb{R}$ and finally, opponent's prior probability is described as b_o, then the discount factor is also presented as γ.

In this paper, the three major modelling assumptions are explained in the following statement:

1) Either adversary or civilian with hostile intents are defined as opponent.

2) A reactive policy modelled the behaviour of civilian opponent, which is self-interested. The policy of reactive is explained as $\pi^{cil}(a_t^o\mid s_t)$.

3) MDP defined the hostile opponent, which is primarily goal-directed.

Consider that the accurate civilian behaviour model is available, and generate the two parameters such as deception level and rationality level with parametric set of hostile models. The policy of the autonomous agent is represented by feed-forward Neural Network (NN), where it takes the input as binary belief states. According to average model, Bayesian filtering the hidden intention to obtain those belief states and produces the stochastic policy as output. To ensure the safety, a state dependent reward and exploring behaviour are encouraged by reward function, which is composed of belief dependant reward.

The exploitability are reduced by soft Q learning algorithm [16], which is used to learn the maximum entropy policy. In the below sections, the brief descriptions of policy learning, agent modelling and belief space reward are presented.

1) *Opponent modelling*

The opponent is either adversary with hostile intents or civilian is denoted by the binary variable, which is described as $\lambda\in\{0,1\}$. The different behaviours are exhibited by the opponent, which depends upon λ and the opponent policy as $\pi^o(a_t^o\mid s_t)$ is fully described. The action probability are dependent only on current state, then this model is act as restrictive. The learned autonomous agent policy is evaluated by dependent opponent policy's general history, and only the policy learning is used by this method. The opponent has full observability, which is illustrated as implicit assumption over the states, where the POMDP agent as opponent modelling released this assumption.

If $\lambda=0$, then opponent is civilian and also assumed that a simple reactive policy $\pi^{cil}(a_t^o\mid s_t)$ is available to model the opponent and the civilian model is presented in Eq. (2).

$$\pi^o(a_t^o\mid s_t,\lambda=0)=\pi^{cil}(a_t^o\mid s_t) \tag{2}$$

Adversary model: In order to model an adversary agent's policy π^o, the following Eq. (3) and (4) are utilized.

$$\pi^o(a_t^o\mid s_t,\lambda=1;\beta)=\arg\min_{\pi\in\Delta}\left\{\begin{array}{l}KL(\pi\mid\pi_a^{MDP})\\+\beta KL(\pi\mid\pi^o(\cdot\mid s_t,\lambda=1))\end{array}\right\} \tag{3}$$

$$\pi_\alpha^{MDP}(a_t^o\mid s_t,\lambda=1)=e^{\alpha Q(s_t,a_t^o)}/Z(s_t) \tag{4}$$

Where, the divergence between two distributions are depicted as $KL(\cdot\mid\cdot)$ and KL is denoted as Kullback-Leibler. The adversary MDP consists of optimal function as $Q(s_t,a_t^o)$, which is associated with goal-achieving policy as π_a^{MDP}. In Eq. (4), the rationality of adversary level is illustrated by temperature parameter called α. The level of deception is indicated by other parameter called β and the partition function as $Z(s_t)$ are used to normalize the π_α^{MDP}.

The known adversary MDP modelled the goal-directed behaviour, which assumed the opponent modelling as $(S^o,A^o,T,O,R^o,\gamma^o)$, where by the action space of the autonomous agent augmented the state space of the active perception problem, which is defined as $S^o=S\times A^a$. Even though the world space S is the same, the opponent will be in different MDP state, where the different actions are carried out by autonomous agent and it also allows the different responses are conducted by opponent. The active perception problem is same as the adversary's action space of MDP is illustrated as A^o and the T is the transition probability. The active perception is different when compared with reward of adversary MDP, that is specified by the reward function R^o. When compared with γ, the discount factor is different and also described as γ^o. The balance between goal actions are defined by the adversary policy, which is obtained by combining the Eq. (3 and 4). In Eq. (3), the adversary MDP is described by the first term, which is corresponding to goal actions, where second term in Eq. (4) defines the deceptive actions by imitating the civilian policy. By varying the two hyper parameters α and β , variety of adversary behaviour is achieved by describing a set of policies, where the active perception policy are optimized to make it robust. Hence, Eq. (5) represents the uniform hyper-prior parameter, which is considered over those two hyper parameters.

$$p(\alpha,\beta)=\begin{cases}1 if\ 1\le\alpha\le2, 1\le\beta\le2;\\ 0\ otherwise.\end{cases} \tag{5}$$

2) *Belief space reward*

A Bayesian filtering is used to maintain the belief $b_t(\lambda)$ over the hidden variable. The both models namely adversary and civilian are required by this reward, where the Eq. (2) explains the civilian model. The inference over the joint space is not useful as well as expensive due to mismatch of real adversary behaviour with this handcraft model, where the adversary model contains two continuous parameters. The Eq. (6) shows the marginalizing the hyper-parameters using an average model.

$$\bar{\pi}^o\left(a_t^o \mid s_t,\lambda=1\right)=\iint \pi^o\left(a_t^o \mid s_t,\lambda=1;\alpha,\beta\right) p(\alpha,\beta)\,d a d\beta \tag{6}$$

With (2) and (6), belief update rule of Bayesian is defined well. The definition for safety and balance exploration is given in Eq. (7), which is a hybrid belief-state dependent.

$$r\left(b_t,s_t,a_t^a\right)=-H\left(b_t\right)+r\left(s_t,a_t^a\right)$$

$$=b\log b+(1-b)\log(1-b)+r\left(s_t,a_t^a\right) \tag{7}$$

Where, $b_t(\lambda=1)$ are denoted by the parameters h and b , which is used to verify that opponent is adversary and the state dependent reward is defined as $r\left(b_t,s_t,a_t^a\right)$. The safety and exploration behaviour is balanced by this reward (7). The $-H\left(b_t\right)$ is described as negative entropy reward that could be interpreted, where the true negative rate (TNR) and true positive rate (TPR) of expected logarithm are maximized. The safety is ensured by the state-dependent reward $r\left(b_t,s_t,a_t^a\right)$. For sample, large negative reward discouraged some actions, which is dangerous to civilians.

3) *Policy learning*

In this research study, soft Q-Learning is used to learn the stochastic belief space policy. The expected reward is maximized by this soft-Q learning objective, where entropy of the policy is regularized and shown in Eq. (8),

$$\Sigma_t E_{b_t,s_t,a_t,\sim\rho_\pi}\gamma^t\left[r\left(b_t,s_t,a_t\right)+\sigma H\left(\pi\left(\cdot\mid b_t,s_t\right)\right)\right] \tag{8}$$

The policy softness is controlled by the parameter σ. The accumulative reward is maximized by this objective function's interpretation while behaving as uncertain as possible, where this objective function is also defined as desired property against an adversary.

The soft-Q iterations are used to solve this maximum entropy problem. The Eq. (9) and (10) defines the fixed point iteration for discrete action space respectively:

$$Q_{soft}\left(b_t,s_t,a_t\right)\leftarrow r_t+\gamma E_{b_{t+1},s_{t+1},\sim\rho_s}\left[V_{soft}\left(b_{t+1},s_{t+1}\right)\right] \tag{9}$$

$$Q_{soft}\left(b_t,s_t\right)\leftarrow \sigma\log\Sigma_{\alpha\in A}\exp\left(\frac{1}{\sigma}Q_{soft}\left(b_t,s_t,a\right)\right) \tag{10}$$

The optimal soft values functions are converged as Q_{soft}^* and V_{soft}^* , and Eq. (11) is used to obtain the optimal policy

$$\pi_{MaxEnt}^*\left(a_t\mid b_t,s_t\right)=\exp\left(\frac{1}{\sigma}\left(Q_{soft}^*\left(b_t,s_t,a_t\right)-V_{soft}^*\left(b_t,s_t\right)\right)\right) \tag{11}$$

IV. Experimental Setup

A. Framework

The compute unified device architecture is used to implement this research work in Python language, where Nvidia is used to create the Application Programming Interface (API) model and parallel computing platform for device architecture. The NNs are developed by using two different libraries: Keras and TensorFlow.

B. Datasets

To validate the performance of proposed method against existing techniques, two datasets: text and image are used in this experimental analysis. From the theory explanations, the proposed DL method has the capacity for solving the issues of various data namely images, text, audio and video.

1) *Datasets for Text*

There are four different types of datasets used to classify the text, where the dataset includes 20Newsgroups, Reuters, WOS and IMDB.

The abstract of academic articles is collected and presented as a Web of Science (WOS) dataset [17]. It contains the documents in three corpora as 5736, 11967 and 46985 for three different number of topics such as 11, 34 and 134.

In the Reuters datasets, the training dataset contains 7769 documents and testing dataset consists of 3019 documents and total 10788 documents, which are divided into total classes of 90.

In this dataset, total 25000 movie reviews are considered for training process and remaining 25000 reviews are used for testing purpose. Hence, IMDB dataset has 50000 highly popular movie reviews. The maximum length of 1000 words presents in total 19997 documents are considered as a 20NewsGroup dataset.

Retrieval Number: B6465129219/2019©BEIESP
DOI: 10.35940/ijitee.B6465.129219
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The validation consists of 4000 samples and remaining 15997 samples are used for testing process.

2) Image datasets

For image classification, two datasets namely MNIST hand writing and CIFAR datasets with ground truth images are considered in this approach, which are described in this sub-section.

The input feature space of MNIST is in the format of 28×28×1 and also it contains the handwritten number as $k \in \{0,1,...,9\}$. The 10000 samples are used for testing process and then, training process uses nearly 60000 data point samples.

CIFAR: There are totally 60,000 images presents in the dataset, with the standard format i.e. 32×32×3 and distributed as 10 classes namely bird, automobiles, horse, airplane, deer, truck, dog, cat, horse and ship. From the overall images, nearly 49,990 images are used as training dataset and remaining images are used for testing process.

C. Analysis of Proposed algorithm by means of document categorization

In this section, the proposed methodology is validated based on the comparison of existing document classification algorithms such as CNN [18], RNN [18], SVM, SVM(TF-IDF) [19], RDML [14]. The comparison of classification algorithm is evaluated in terms of classification accuracy with respect to various document datasets. Table 1 presented the validated results of various classification algorithms with proposed method by means of classification accuracy for different document datasets. After the analysing the Table 1, when compared with existing document classification algorithms, the proposed DL method performed better performance.

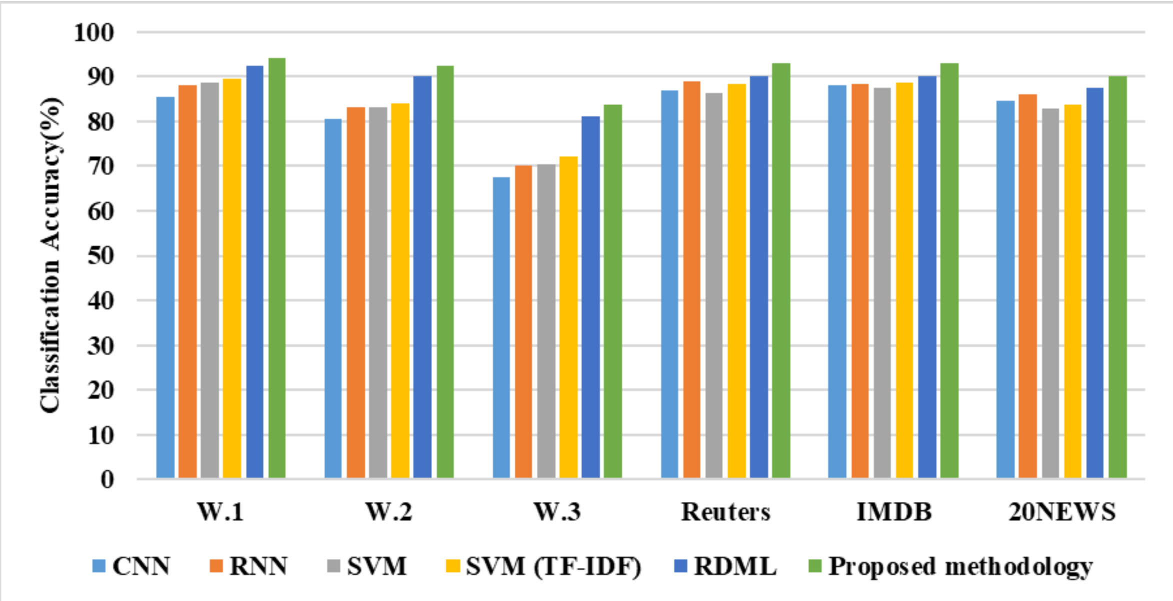

Figure 2. Comparative analysis of classification algorithms on various text datasets

Table 1. Numerical analysis on the document classification accuracy

	W.1	W.2	W.3	Reuters	IMDB	20NEWS
CNN	85.54	80.65	67.56	86.9	87.97	84.57
RNN	88.24	83.16	70.22	88.93	88.45	86
SVM	88.68	83.29	70.46	86.30	87.44	82.91
SVM (TF-IDF)	89.46	83.96	72.12	88.40	88.59	83.75
RDML	92.42	90.16	81.14	90.01	90.27	87.42
Proposed methodology	94.21	92.42	83.65	92.95	93.09	90.01

D. Analysis of proposed algorithm by means of image classification

In this sub-section, the validation of the proposed DL method were carried out by comparing the performance of an existing document various classification algorithms. The comparison of classification algorithm is evaluated in terms of classification error respect to MNIST and CIFAR-10 image datasets. The numerical analysis on error rate of the of various those classification algorithm with respect to two datasets are presented in table 2. By analysing the table 2, it is concluded that the proposed methodology performed better than the existing document classification algorithms.

Table 2: Numerical analysis on error rate of the of various classification algorithm

	MNIST	CIFAR-10
Deep L2-SVM	0.86	11.5
Maxout Network	0.93	11.58

BinaryConnect [20]	1.25	9.7
PCANet-1 [21]	0.64	20.31
gcForest [22]	0.72	21.29
RDML [14]	0.32	9.11
Proposed methodology	0.21	8.59

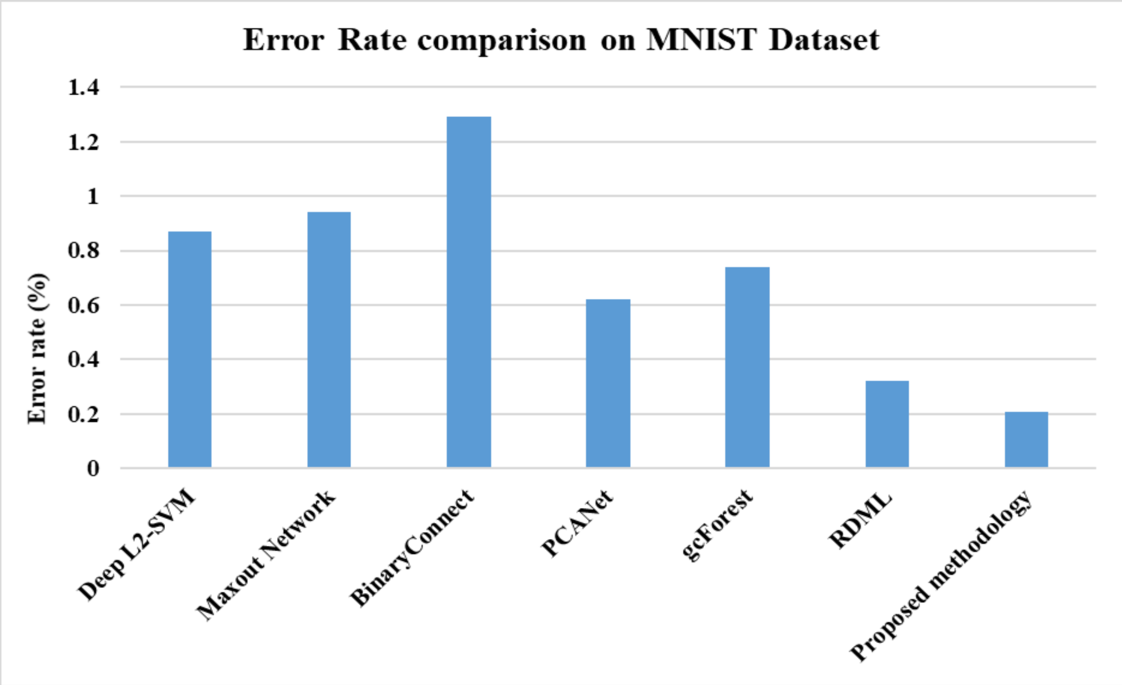

Figure 3: Comparative analysis of error rate on MNIST dataset

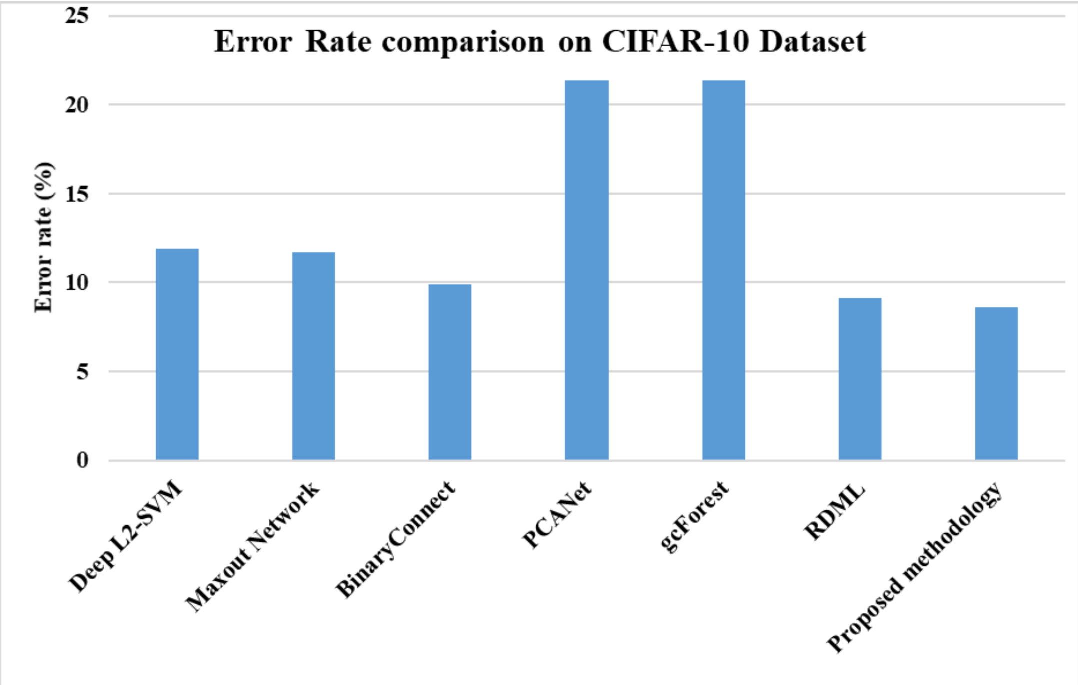

Figure 4: Comparative analysis of error rate on CIFAR-10 dataset

V. DISCUSSION AND CONCLUSION

When the number and size of datasets are largely increased, sophisticated classification is needed. But, the task of classification is one of the major problems, that should be addressed by developing a new machine learning techniques. In this research, multi-model classification algorithm is presented to attain the stochastic belief space policy by combining the maximum entropy RL, belief space planning and generative adversary modelling. When compared with unmodeled adversarial strategies, the autonomous agent action prediction is minimized and achieved robustness by using various adversarial behaviours in the simulation framework. The proposed reinforcement based DL algorithm can be used as multi-model classification purpose.

The single neural network algorithm can perform the classification on text data and image data. The RL learns the appropriate belief space policy from the feature extracted information of the text and image data. According to the feature of the input data, the belief space policy is generated based on the maximum entropy computation. While comparing the effectiveness of the proposed method against conventional techniques such as single DL or SVM model. The experiments were carried out on different datasets namely IMDB, Reuters, WOS, CIFAR, 20NewsGroups and MNIST. From the validation results, majority vote is used to classify the datasets for providing flexibility and also showed that the improvement of proposed DL methods in classification results. Even though, the proposed DL method attained classification accuracy in a satisfaction rate, the hybrid effective models should be developed in future for improving the accuracy in a different range of data types and applications.

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