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Comparative analysis for augmented decision-making applications using deep learning models

P. Durga[1] and S. Karthikeyan[2*]

[1]School of Computer Science and Engineering, VIT-AP University, Amaravati, Andhra Pradesh 522237, India
[2]School of Computer Science and Engineering, KPR Institute of Engineering and Technology, Arasur, Tamil Nadu 641407, India

[*]Corresponding author; E-mail: skarthi.sns@gmail.com

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Abstract

Now a days decision-making plays a significant role in various applications and several research. For applications such as diseases, intelligent routing systems, and online shopping carts such as e-commerce sites, recommended systems are developed based on sentiment analysis (SA) and take accurate decision-making based on the predictions and analyze the accurate decisions based on the result analysis. When it comes to practical uses, deep learning (DL) has by far been the most popular. DL becomes an indispensable domain for several tasks in science and engineering. It is very difficult to take decisions based on traditional tests in various research areas such as disease prediction, textual sentiment analysis, and risk prediction of autonomous vehicles due to the lack of accuracy and long time for results. To address this, various approaches are proposed to adopt. Decision-making is based on multi-criticism, which is more useful to solve critical issues in making accurate decisions than previous approaches. In this paper, an improved and augmented decision-making deep learning algorithm is discussed and shows the comparison among the various DL algorithms. The performance is calculated according to the parameters.

Keywords: *autonomous vehicles; decision making; deep learning; disease prediction; risk prediction; sentiment analysis.*

1. Introduction

Computer scientists and engineers alike have shown a lot of interest in decision-making systems (DMS) that employ deep learning (DL) methods (Otter et al., 2020). AutoML is used in a wide variety of popular applications, including e-commerce, social networking sites (SNS), sentiment analysis (SA), and autonomous vehicles (AV) (Wang et al., 2020; Aradi, 2020). AutoML is also used to predict diseases by analyzing patients' health conditions and to predict risk for DM in AVs (Lu et al., 2020). With the help of DMS in E-commerce, researchers can easily find the most well-liked items on the site by analysing user ratings, comments, and other data.

The success of the product is taken into account when making a final choice. In the context of disease prediction, DMS is used to assess the current state of diseases based on the available data. Disease prediction can be accomplished in a number of ways, including by analysing the dataset (patient details), analyzing the CT scan images, analysing the X-ray images, utilizing DL with image processing to diagnose skin diseases, diagnosing Chronic Kidney Disease (CKD), and detecting brain tumors (Li et al., 2020a; Qin et al., 2019; Noreen et al., 2020). One other field that has the potential to improve disease prediction is artificial intelligence (AI). Artificial intelligence (AI) is crucial for the diagnosis and prognosis of disorders like COVID-19. Insight into the COVID-19 virus is greatly enhanced by the incorporation of AI and DL (Jamshidi et al., 2020). COVID-19 disease diagnosis also necessitates effective training, and different datasets are used for both (Oh et al., 2020). The DMS also looked into ways to detect life-threatening conditions like heart disease and chronic illness (Ge et al., 2020; Li et al., 2020b). The diagnosis of chronic diseases is also the topic of several algorithms. Several individuals have been having extensive conversations regarding COVID-19 on social media (Li et al., 2020c; Elhadad et al., 2020). On occasion, COVID-19-related misinformation is also disseminated via social media. The integration of DMS and DL is the primary focus of this study because it shows promising outcomes in illness prediction (Arockia, Panimalar, & Krishnakumar, 2023). This can sometimes reveal the disease's progression, provide reliable sentiment analysis in a variety of disciplines, and facilitate the operation of autonomous cars.

1.1 Literature survey

The integrated automatic ML (AutoML) approach for risk prediction and behavior assessment was first introduced by Shi et al. (2020). AutoML is a model for predicting safe and effective behaviors in autonomous cars, emphasizing decision-making (DM) and motion trajectory planning (AVs). The comparison between the proposed model and the other three risk predicting AutoML models demonstrates that it has the highest predictive power (91.8% accuracy). Several crucial aspects are highlighted to improve the suggested model's accuracy and other metrics.

Several DL methods were discussed by Muhammad et al. (2020) that perform well in real-time settings. Advanced AI and DL are employed across domains to address a range of accuracy concerns. This model's eventual goal is to connect Intelligent Transportation Systems (ITS) and DL-based AD safely to deliver reliable suggestions.

Using the actor-critic (AC) method, with tools like deterministic policy gradient, Fu et al. (2020) suggested a new DM technique to address the barking problem (DDPG). This program takes autonomous driving through a progression of phases that demonstrate the effect on several performance metrics, including precision and responsiveness. Advances in autonomous driving are possible with the use of deep reinforcement learning (DRL) (Kraising et al., 2022).

The novel deep learning method developed by Arabneydi & Aghdam (2020) incorporates an AI-based strategy. The agents are crucial to this method's success at lowering function costs. A novel dynamic approach is created to determine the optimal and suboptimal solutions for the first and second variables, respectively, with the aim of enhancing performance. In the end, the proposed method prioritized speed and displayed increased precision.

Diseases are now categorized in a different way because of work by Islam et al. (2020). This method categorized health care into four distinct domains: disease diagnosis and tracking, epidemic prediction, sustainable development, and disease detection. Radiographs of the chest and computed tomograms are used in the experiments. The proposed procedure enhances the speed and accuracy of COVID-19 diagnosis and treatment.

Yang et al. (2020) developed a new combination technique that merged sentiment lexicon with bidirectional convolutional neural network (CNN) and attention-based Bidirectional Gated Recurrent Unit (BiGRU). The suggested technique employs weighted sentiment characteristics to retrieve the crucial data points. A Chinese online marketplace is used to test the proposed model. The precision of the system was enhanced by the new proposal.

A novel sentiment analysis, proposed by Chakraborty et al. (2020), is used on data gathered from social media platforms. The method was designed to identify people with similar profiles based on their preferences.

In 2020, Wang et al. presented a novel method for categorizing the classification of social media content as favorable, bad, or neutral. The system is commonly referred to by its acronym, "BERT" (Bidirectional Encoder Representations from Transformers). The TF-IDF is used to enhance BERT's functionality. Thematic analysis is utilized to demonstrate accurate feelings based on patterns. Multiple users' sentiments toward COVID-19 are analyzed using this model.

For their suggested roadway decision-making technique, Liao et al. (2020) developed a novel DL model that incorporates the dueling deep Q-network (DDQN) algorithm. A contrast is made between the DDQN and deep Q-network algorithms. In comparison to prior methods, the proposed model performs quite well.

In order to describe the general DRL, Aradi (2020) created a novel model that is capable of solving the hierarchical motion planning problem. With the use of computational specs, we are able to calculate a number of different car types. There are a number of strategic choices at various levels of development in this model.

An updated ensemble approach was proposed by Qin et al. (2019) to better detect and diagnose CKD. The machine learning repository at UCI in California is used as a testbed for the proposed model. To fix the missing value problems, the dataset needs better pre-processing. The results of the studies demonstrate that out of the six ML algorithms tested, RF achieved the highest accuracy (about 99.86%), followed closely by the hybrid model (99.97%).

An ACWGAN-GP method was proposed by Li et al. (2020) to generate large-scale, high-quality samples by exploiting the imbalance in the training data. The primary goal here is error diagnosis. A new method for problem diagnostics based on sequence labeling technology was proposed by Chen et al. (2021). Air compressor malfunction diagnosis can be performed using this method. The author additionally provides contrasting examples. A new ensemble learning approach, introduced by Alojail & Bhatia (2020), provides in-depth user-beneficial product analysis. This method, which is based on customers' actions in stores, has proven effective. The novel lane identification model presented by Wang et al. (2020) will be utilized by many autonomous vehicles to identify lane boundaries. This method is a curve-based method that improves highway curve and straight-line recognition. As Liu et al. (2019a) and Liu et al. (2019b) pointed out, sentiment analytics can be used in a wide range of contexts. In contrast to standard prediction methods, transfer learning in sentiment analysis yields more precise results while also resolving other domain-specific problems. An expert system called machine learning-based back-propagation neural networks (MLBPNN) was presented by Shakeel, et al. (2020). Using infrared sensor imaging technology, this approach is unified. Classifying brain tumors will go well with this method. The bidirectional convolutional neural network (CNN) suggested by Onan (2022) makes use of two independent bidirectional LSTM and Gated Recurrent Unit (GRU) layers. To increase the performance feature extraction is used to extract the high-level features and also used to reduce the dimensions of the dataset. Several large datasets are used to find the sentiment analysis on various domain datasets. The proposed approach achieved better results based on performance. Onan (2022) consensus clustering based-undersampling approach (CCBUA) is used to solve the class imbalance issue which is occurred with ML algorithms. Several real-world datasets are used to process the imbalanced datasets such as the diagnosis of medical information, detection of malware, filtering of spam, etc (Sanson et al., 2020). The experiments are conducted by using the five ML algorithms with the ML algorithms that are applied to real-time datasets. Onan et al. (2016) presented several comparative ML approaches that are used for text classification of various text documents. The ensemble algorithms got the better text classification among the existing algorithms. Onan et al. (2017) proposed an ensemble feature-based selection model that extracts the significant features that are used in the classification of sentiments. Onan & Toçoğlu (2021) presented the ensemble architecture that consists of TF-IDF with CNN-LSTM. This approach consists of 5 layers that are used to analyze the sentiments based on attributes, opinions, ideas, etc. Based on the sentiment analysis the decision-making is applied to find accurate opinions.

Onan et al. (2017) proposed a hybrid model that focused on clustering and random search based on the classification of text. The clustering is divided into two groups based on the properties present in this system. The proposed approach shows better accuracy based on clustering. Ding et al. (2022) presented the RNN model for analyzing opinion mining based on instructor analysis reviews. The proposed approach is applied to 154,000 reviews that are collected from various online sources. The comparison between various ML algorithms shows that RNN is a better algorithm with better text classification. Onan & Toçoğlu (2021) introduced the three-layer stacked LSTM that finds sarcastic text files. The proposed approach shows significant results when it is applied to a real-time documents dataset. Onan (2018a and 2018b) proposed the focus on showing the four types of classifiers merged with a swarm-optimized model that gives better results. Thota Ramathulasi & Rajasekharababu (2022) proposed the various text classification models which is called Augmented latent Dirichlet allocation model (AUG-LDA). The proposed approach uses the LDA as training based on word vectors. Several tools such as the word2vec tool are used to extract accurate word classification. Onan (2018a and 2018b) proposed a new feature extraction approach that extracts accurate features from the datasets. Onan (2019a and 2019b) presented the DL approach that finds sarcasm. The proposed approach is applied to Twitter data containing 5k to 30k messages (Onan & Korukoğlu, 2017; Onan, 2021).

Based on the literature survey it is observed that the authors proposed and implemented various algorithms that are related to sentiment analysis. According to the analysis, decision-making is applied to every application and research in this section. Decision-making is more capable to analyse the experimental results and obtaining better predictions based on the reviews, ideas, etc. A general workflow of implementing deep learning algorithms in practical decision-making systems is illustrated in Figure 1.

2. Objective

- To predict and analyze accurate decisions in various applications and several research based on the result analysis for applications such as diseases, intelligent routing systems, and online shopping carts.
- Using deep learning, solve critical issues in taking accurate decision-making among previous approaches.
- An improved and augmented decision-making deep learning algorithm is discussed.

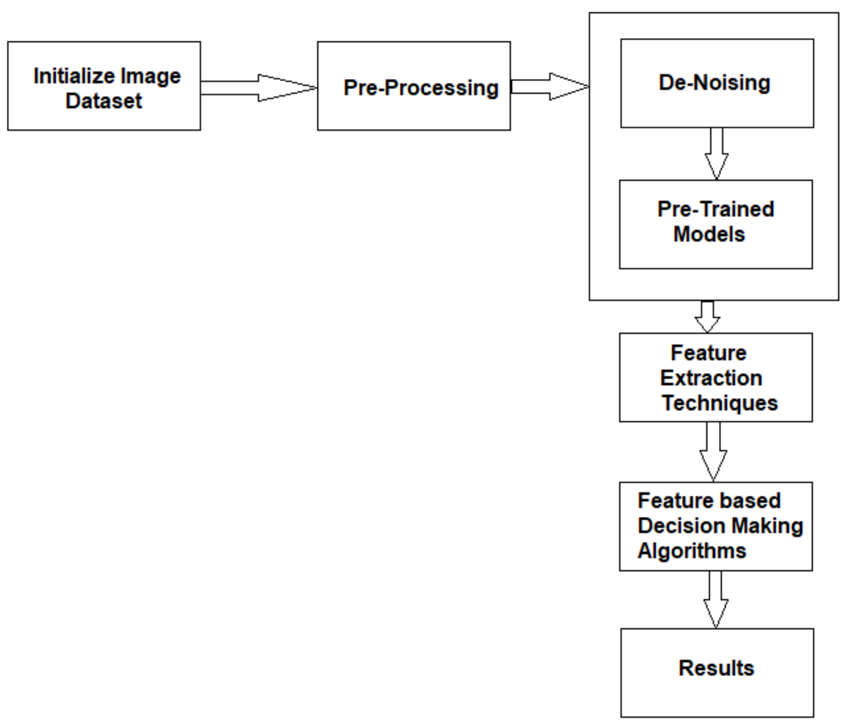

Figure 1 Implementing deep learning algorithms in practical decision-making systems

3. Methodology

3.1 Important variants of deep learning: Architectures

Many sophisticated applications rely on Deep Learning (DL) to address a wide range of problems. Sub-domain Learning Machines (ML). Accurate classification is essential in many real-world applications, and DL techniques like CNNs, RNNs, GANs, and Attention Mechanism models are frequently employed to achieve this goal. Preprocessing, feature extraction and result analysis are only some of the common data processing activities that are baked into every model's layers. Unmanned vehicle operation has emerged as a major challenge for the automotive sector. When changing lanes, autonomous vehicles make decisions using onboard computers, which has the obvious safety benefit, but the analysis of key aspects in lane changes is often overlooked (Liu et al., 2019a and 2019b). Market research, disease forecasting, driving a self-driving car, etc. are just a few of the numerous places where sentiment analysis (SA) is put to use. When it comes to assessing consumer transactions in order to provide more discounts, the combined deep learning architecture performs admirably. User credit scores can be calculated using full-connected long short-term networks (FC-LSTM), which are based on the LSTM attention mechanism (Ling et al., 2019). Prognostics and Health Management (PHM) is another promising area where DL plays an important role (Wang et al., 2018). Hyperspectral image (HSI) categorization utilizes a stacked autoencoder trained with a deep learning (DL) approach for detecting outliers (Zhang et al., 2019; Wan et al., 2019; Li et al., 2019).

3.2 Decision making

Decision-making in which the best possible option is picked. When there are too many features or not enough observations, the DM procedure gets more difficult. When constructing a model for making decisions, it is crucial to use appropriate features. In order to make better decisions, DM frameworks must enhance categorization accuracy (Haq et al., 2019). Table 1 summarizes the construction of CNN and other DL algorithms that, depending on the dataset, have mostly utilized these layers.

Table 1 Methodologies used in several real-time datasets.

Authors	Domain	Dataset	Algorithms Used
Liu et al. (2019a and 2019b)	Sentiment Analysis	Stanford Sentiment Treebank, Yelp, Multi-Domain Sentiment, Sentiment140 (STS)	Cross-domain transfer learning
Ling et al. (2019)	Online Ticketing	Data collected from a large and famous concert hall in China	Multi-Channel Browsing with FC-LSTM
Wang et al. (2018)	Online Banking	P2P lending platform in China	AM-LSTM
Zhang et al. (2019)	Medical Analysis	CNN and RNN	C-MAPSS and PROGNOSTIA
Wan et al. (2019)	Outlier detection	Stacked Autoencoder (SAE)	Four datasets are ADIAC, Chlorine concentration (Chl), FordA, Mallat.
Li et al. (2019)	Medical Data Analysis	Social Media Dataset	DL Algorithms

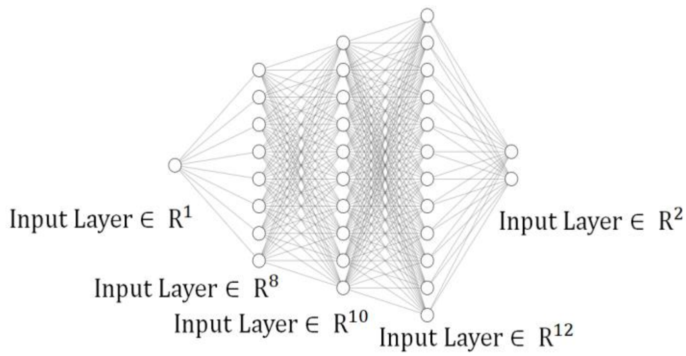

Figure 2 Deep learning structure

Figure 2 consists of three layers the input layer, the hidden layer, and the output layer. In the input layer, there consist of N inputs and input is in the form of vectors through time t such as {…..{at − 1, at, at + 1…}} where at =(a1, a2, a3,..., an). The units of the input layer are strongly connected to the hidden layers. In every hidden layer, the units are divided by using the weight matrix WIH. When the variables are linked together, we can write the hidden layers as ht = (h1, h2,...,hX), where X stands for the number of hidden units. Each level of the concealed layer is defined as:

$$h_t = f_H(O_t) \tag{1}$$

where

$$O_t = W_{IH}a_t + W_{HH}a_{t-1} + b_k \tag{2}$$

The activation function is represented as fH(.) for the hidden layer, b_h- initializes as a bias vector for the hidden layers. The connectivity between the output layer and the hidden layer makes use of the weighted connections W_{HO}. 'P' consists of elements $y_t = (y_1, y_2, y_3, \ldots. Y_p)$ belonging to the output layer:

$$y_t = f_o(W_{HO}h_t + b_0) \tag{3}$$

where $f_o(.)$ represents the activation function and b_o the bias vector of the output layer.

3.3 Activation function

The activation function of each node is coupled in neural networks (Banerjee et al., 2021) with the activation function of the output node, which is the node that gives the actual input or collection of inputs. This allows the network to function properly. Among the several activation functions that can be employed for the NN, "sigmoid" and "tanh" are the ones that are utilized the most frequently. The activation function that was being used in the output layer was combined with the loss function so that the classification model could be trained. The activation functions are illustrated here as

$$\tanh(a) = \frac{e^{2a}-1}{e^{2a}+1} \text{ And } \sigma(a) = \frac{1}{1+e^{-x}} \tag{4}$$

The scaled "sigmoid" is represented as

$$\sigma(a) = \frac{\tanh\left(\frac{x}{2}\right)+1}{2} \tag{5}$$

3.4 **Loss function**

When comparing the actual output bt to the desired output ct, the loss function characterizes the effectiveness of the network as follows:

$$L(b, c) = \sum_{t=1}^{T} L_t(b_t, c_t) \tag{6}$$

3.5 Feature extraction

One of the most important methods for distilling a large dataset into useful characteristics is this one. The big dataset is reduced in dimension via dimensionality reduction so it can be processed more efficiently. One of the benefits of deep learning is that features may be automatically extracted from unlabeled data like photographs and text (Banerjee et al., 2022). Training the network results in the extraction of features. To avoid overwhelming the network with data, it's best to feed it only the input

(Banerjee et al., 2021). The extraction of several features and application of the method has a significant effect on results.

3.6 Performance metrics

Throughout the experiments, Python has been used as the primary language of choice. Python has a wealth of high-powered libraries like sklern, pandas, Keras, and others that make it possible to efficiently run deep learning algorithms. Many different types of data sets, including those from the fields of e-commerce, film criticism, driverless cars, illness forecasting, and more. Any imaginable data set can be analyzed using Python's extensive library support.

3.7 Performance analysis

The calculation of the performance analysis relies heavily on the usage of a confusion matrix.
True positives (TP) occur when the value anticipated actually comes true.

The anticipated value is false, as in a true negative (TN).

In the case of a false positive (FP), the anticipated answer is yes, but the underlying condition is false. Negative predictions that turn out to be correct are called false negatives (FN).

$$\textbf{Precision}=\frac{\text{No. of TP}}{\text{No. of TP+No. of FP}}$$

Accuracy: The overall accuracy is calculated by this measure.

$$\textbf{Accuracy}=\frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$$

Recall: This measures the overall true positives that are found.

$$\textbf{Recall}=\frac{\text{No of TP}}{\text{No of TP+ No of FN}}$$

Specificity: To what extent erroneous values are correctly identified as a whole will be measured.

$$\textbf{Specificity}=\frac{\text{No of TN}}{\text{No of TN+ No of FP}}$$

F1-Score: Incorrectly identified cases can be measured more precisely using the symphony mean of Precision and Recall as compared to Accuracy alone.

$$\textbf{F1-Score}=2^*\ \frac{\text{(Precision*Recall)}}{\text{(Precision+Recall)}}$$

4. Result and Discussion

Python, and occasionally the statistical programming language R, are used for the actual implementation. In Python, you may use a number of different libraries, including sklearn, pandas, matplotlib, Keras, and many more. When working with huge datasets, the system needs at least a 10 GB hard disc and an I5 processor. Accuracy (A), Precision (P), Sensitivity (Sen), Specificity (Spc), Area under the curve (AUC), and F1-Score are the illustrative performance metrics (F1S). The results achieved by several deep learning approaches when applied to a number of datasets are analyzed and tabulated in Table 2 & 3 and illustrated in Figure 3.

Table 2 Results achieved by several deep learning approaches when applied to a number of datasets

S. No	Author	Algorithm	Dataset	Remarks
1	Haq et al. (2019)	Support Vector Machine (SVM)	Parkinson's disease (PD)	The proposed method SVM) can be employed to accurately predict the PD and can be effortlessly integrated into healthcare for diagnosis objectives.
2	Ju et al. (2017)	R-fMRI	Synthetic dataset	Correlated with traditional procedures, the proposed technique has attained about 20 percent of advancement in classification accuracy. This should be applied to real-time datasets.

Table 2 Cont.

S. No	Author	Algorithm	Dataset	Remarks
3	Iqbal et al. (2021)	Deep learning long short-term memory (LSTM) and Residual Net (ResNet − 101)	Prostate Images dataset	The performance measures are improved with K-NN Cosine for GLCM features employing Machine learning classifiers. Outcomes describe that the pre-processing strategy yields satisfactory results
4	Chenyang & Chan. (2020)	Joint Network Adopt a 3-D Encoder-Decoder Architecture	LIDC-IDRI dataset	Test obtaining the LUNA16 and LIDC-IDRI datasets demonstrates that the proposed nodule detector transcends the state-of-the-art algorithms and yields good performance as classification alone is deliberate.
5	Mohan et al. (2019)	Hybrid Random Forest with a Linear Model (HRFLM)	Cleveland Heart Dataset	The suggested hybrid HRFLM technique is manipulated by incorporating the aspects of Random Forest (RF) and Linear Method (LM). HRFLM substantiates to be relatively accurate in the prediction of heart disease.
6	Geweid & Abdallah (2019)	Improved Support Vector Machine (ISVM)	ECG Database	An improved support vector machine (ISVM) that is based on the duality optimization (DO) technique is used in the new method that is described in this article to diagnose heart failure disease (HFD). The results of this method were deemed adequate when compared to other methods.
7	Jeong & Yi (2020)	Bi-directional long short-term memory (Bi-LSTM) module	NGSIM (Next Generation Simulation Program)	The vehicle test results reflected that the proposed predictor can monitor the subject vehicle more safely than the CTRV model and diminish the control action considerably.
8	Gao et al. (2020)	Vector representation learning	CTD base	This is used to treat similar diseases to the patients

Table 3 Performance of several methods

Performance Measure	**SVM**	**R-fMRI**	**LSTM and ResNet**	**A 3D encoder-decoder architecture**	**HRFLM**	**ISVM**	**(Bi-LSTM**	**Vector representation learning method**
Accuracy	93%	86.47%	99.48%	90.29%	88.4%	94.97%	-	86.8%
Sensitivity	90.2%	81.5%	98.33%	88.79%	92.8%	89.4%	54.5	-
Specificity	92.1%	92.03%	100%	91.78%	82.6%	68.1%	-	-
Precision	91.5%	-	-	-	90.1%	66.1%	74.5%	-
F1-Score	91.2%	-	-	-	90%	-	-	-
AUC	-	-	-	-	-	-	97.52%	-

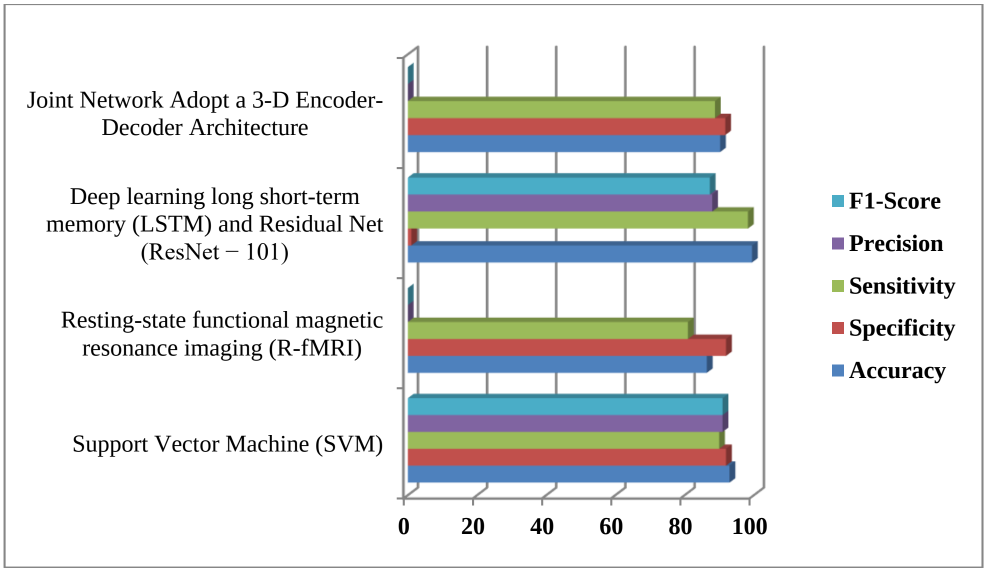

Figure 3 Evaluation of deep learning models on a number of datasets

5. Conclusion

In this paper, numerous decision-making systems (DMS) are discussed by research and used in many applications that are related to public domains to take appropriate decisions. Now a day's decision based on traditional tests in various research areas such as disease prediction, textual sentiment analysis, and risk prediction of autonomous vehicles (AVs) is difficult due to the lack of accuracy and long time for results. This paper focused on various domains such as disease prediction, risks in autonomous vehicles and finding the sentiment analysis in online shopping carts. The performance of existing algorithms is measured with several parameters such as f1-score, precision, sensitivity, specificity, and accuracy. According to the datasets and algorithms, the parameters are measured. Among all the existing algorithms DL-LSTM_ResNet-101 shows better performance with an accuracy of 99.48%, Sensitivity of 98.33%, and specificity of 100%.

In the future, an ensemble DL algorithm is to be developed to take accurate decisions for disease prediction, autonomous vehicles and E-commerce applications. These ensemble algorithms improve the performance based on the disease detection rate and improved metrics.

Declarations

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Conflict of Interest

The authors have stated that there are no competing interests between themselves and this study. We thus state that we do not have any commercial or associative interests that could be construed as a potential conflict of interest in relation to the work that has been submitted.

Availability of data and material

Not applicable

Code availability

Not applicable

Author contributions

The author who is listed as the corresponding author asserts that they made the most significant contribution to the paper, including its formulation, analysis, and editing. Editing of the paper and advice on how to validate the results of the analysis are provided by the second author.

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