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A SYSTEMATIC LITERATURE REVIEW OF DEEP AND MACHINE LEARNING ALGORITHMS IN BRAIN TUMOR AND META-ANALYSIS

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ABSTRACT

Brain tumor (BT) is considered one of the dangerous conditions that could strike both adults and children. 85 to 90% of all primary malignancies of the "Central Nervous System (CNS)" are Brain Tumor. Each year, brain tumors are discovered in approximately 11,700 persons. The 5-year survival rate for patients with malignant brain or CNS tumors is around 36% for women and 34% for men. The current systematic review depends on "the Preferred Reporting Items for Systematic reviews and Meta-Analysis statement" and 40 appropriate studies. The search of the literature employed search engines similar to: IEEE Xplore, Google Scholar, Hindawi, PubMed, SCOPUS, Wiley Online, Web of Science, Taylor and Francis, Science Direct, and Ebscohost. This study concentrated on four characteristics: Algorithms of Machine and Deep Learning, best- algorithm performance, datasets, and application used in Brain Tumor predictions. The experimental articles did not use Reinforcement Learning, Semi-supervised learning, and promising aspects of Deep and Machine Learning. Algorithms based on ensemble technique exhibited sensible rates of accuracy nonetheless were not frequent, whereas Convolutional Neural Network (CNN) were well epitomized. A few studies smeared main datasets (13 of 40). Logistic Regression (LR), Deep Neural Network (DNN), boosting algorithms, Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), were the best performing algorithms. This review will be beneficial for investigators predicting Brain Tumor using machine and deep learning methods.

Keywords:- *Brain Tumor, Datasets, Deep Learning, Machine Learning*

1. INTRODUCTION

The amount at which individuals are passing away due to Brain Tumor is overwhelming, with the WHO assessing yearly 251,329 losses worldwide. In low and middle-income countries, the total of individuals who pass away from brain tumors has doubled three times as stated by "the National Brain Tumor Foundation (NBTF)" [1].

A brain tumor is one of the most serious conditions that adults and kids are both affected by. Brain tumors constitute 85% to 90% of "the primary Central Nervous System (CNS)" cancers. Each year, brain tumors are diagnosed in about 11,700 patients. "The 5-year survival rate for patients with a malignant brain or CNS tumor is approximately 34% for men and 36% for women. Brain tumors are divided into benign, malignant, pituitary," and other subtypes. Appropriate care, meticulous planning, and accurate diagnostics are required to prolong patient lives. Magnetic resonance imaging (MRI) is the most efficient way for detecting brain tumors [2].

Prompt discovery and diagnosis are acute for decreasing the Brain Tumor problem. Artificial-intelligence (AI), a subfield of computer science, places a strong emphasis on the creation of hardware and software with intelligence that resembles human behavior. Computer programs that have been upgraded with artificial intelligence are capable of learning, planning, and problem-solving activities, among others.

Benefits of AI are numerous as recognized in the literature [41-45]. These comprise helping specialists do complex operations, appropriate decision-making, and jobs, to provide precise Brain Tumor in images, to decrease the threats of composite handlings, to enhance Brain Tumor knowledge about individual behavior, and enhancing computer assistance identification [3]. AI, Machine Learning (ML) and Deep Learning (DL) research concentrate on in-expensive, fast, and non-invasive approaches to precisely detect Brain Tumor using advanced metrics of performance likes: sensitivity, Recall, Accuracy, F1-Score, Precision, and specificity [4].

Machine and deep learning permit PCs to discover, calculate, and understand relationships among attributes to increase preventive medicine by analytically learning ideal data representations [5, 46-48]. Deep learning processes can examine through substantial volumes of Brain Tumor data, permitting it to discover prognostic, diagnostic, and remedial treatment options for various Brain Tumors easily. The most popular types of deep learning techniques are: supervised, un-supervised, reinforcement and Semi-supervised learnings [6, 49-50]. Supervised-learning is a vigorous method that uses computer language to categorize and understand labeled Brain Tumor data [7, 51]. Such as, in supervised learning, a specialist may pursue to identify whether an image represents benign, malignant or pituitary? Consequently, supervised-learning needs a dataset with images and pre-defined labels [8, 52-53]. Unsupervised-learning aims to discover the principal construction or relationships among attributes in a given data set [9]. This data set will be trained with no labels for the images, and the model gathers the data to categorize the essential arrangements. According to behavioral consciousness, reinforcement-learning uses another approach in which a software functions in a pre-determined setting to maximize a return. Semi-supervised-learning is a deep learning method that blends a large volume of unlabeled data with a small volume of labeled data throughout the training. It lies between un-supervised and supervised learning.

The focal aim of the current Systematic Literature Review (SLR) is to identify which supervised-learning procedures show the top outcomes for Brain Tumor forecasting. In current SLR: 1) the researchers identified articles that used deep-learning methods to identify Brain Tumors; 2) to recognize the top employed supervised-deep-learning procedures for BT forecasting; 3) to assess the supervised deep learning procedures performance of in relation to the designated measures for example sensitivity, F1-Score, Recall, specificity, precision, and Accuracy; 4) to investigate the data sets for the prediction of Brain Tumors. The results of this SLR will give authors the guideline, training, and additional research on Brain Tumor. The reset of the paper is organized like this: Section 2 will present the Methods and Materials, Section 3, outline the Review of the Literature, Section 4, provide detailed Discussions, and the concluding section present the Conclusion and futures of work [10].

2. METHODS AND MATERIALS

The embraced procedure in this SLR is “the Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA) statement”. The PRISMA is a group of components employed to describe SLR and analyses [11]. It is envisioned to support report analyses and arbitraries trial measurement [12], furthermore, it could be used as a basis for a systematic reviews reporting [13]. By applying the PRISMA method, this current study took into consideration a few research questions directing the SLR, criteria for the searching of literature, and selection criteria.

2.1 Search Criteria of the Literature

The criteria of selection recognized important review articles and published research by means of key terms for example Brain, Tumor, Brain Tumor disease, Brain Tumor problems, artificial intelligence, deep learning algorithms, deep learning techniques, data mining, machine learning techniques, machine learning methods, and in Brain Tumor. The study embraced combined search criteria literature that associates key terms by applying operators of boolean like “and, or, --, ~”. Among the search engines employed includes: Science Direct, Ebscohost, Google Scholar, SCOPUS, Hindawi, Web of Science, Wiley Online, IEEE, PubMed, Taylor and Francis. Thus, the search result produced approximately 640 research articles, 40 of them were considered suitable depending on the selection criteria in the current study.

2.2 Selection Criteria

Our study employed published research papers written in the English language. Table I shows inclusion and exclusion criterion employed in our study. The found research articles concentrated on the Deep and Machine Learning application methods in examining Brain Tumor. The criteria selection omitted non-research papers like Thesis, chapters, and books were omitted from the SLR.

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Table 1. Paper Selection Criteria

Feature	Criteria Inclusion	Criteria Exclusion
Publication Language	English	Not English
Type of Research	Research Papers	Thesis/Dissertation, case studies, books, reports, and magazines.
Focus of Research	Techniques related to DL, ML in Brain Tumor	Not in relation with DL, ML and Brain Tumor
Setting	Worldwide	(N/A)

3. RESULTS

A search of the literature in aforementioned databases recognized 640 articles (as in Figure 1). Sorting via abstract indicates 350 articles did not match the criteria selection for the current literature review. Further sorting by title showed 170 articles did not comply with the focus of the systematic review. On the other hand, complete text sorting of the leftover articles show 50 research papers were connected and they were not using DL and ML methods to Brain Tumor. Consequently, those articles were left out from the last listing. To conclude, 40 research papers on the application of DL and ML procedures in Brain Tumors were contained within the current review.

The list of references in Table 2 shows 40 articles used in the current SLR. From the previous studies, the focus area of those papers were: 1) Prediction of Brain Tumor, 2) detection of Brain Tumor, and 3) diagnosis of Brain Tumor by DL and ML methods. A substantial quantity of those articles meant Brain Tumor prediction methods. The collected papers covered the years from 2015-2021. Figure 2 portrays the ratio of the gathered research papers on the occurrence over the time. The count of research papers has varied gradually with time with the exception of from 2019 to 2020, that show a substantial upsurge (from 7 to 11 articles) and a decrease from 2020 to 2021 (from 11 to 8).

The search outcomes discovered no articles on predictions of Brain Tumor via DL techniques in 2014 and prior 2013. That might be clarified by the restricted admittance to open access data sets and the debatably evolving of DL approaches prior 2013. The amount of research papers in this case reduced from 11 articles in the year of 2020 to 8 articles in the year 2021.

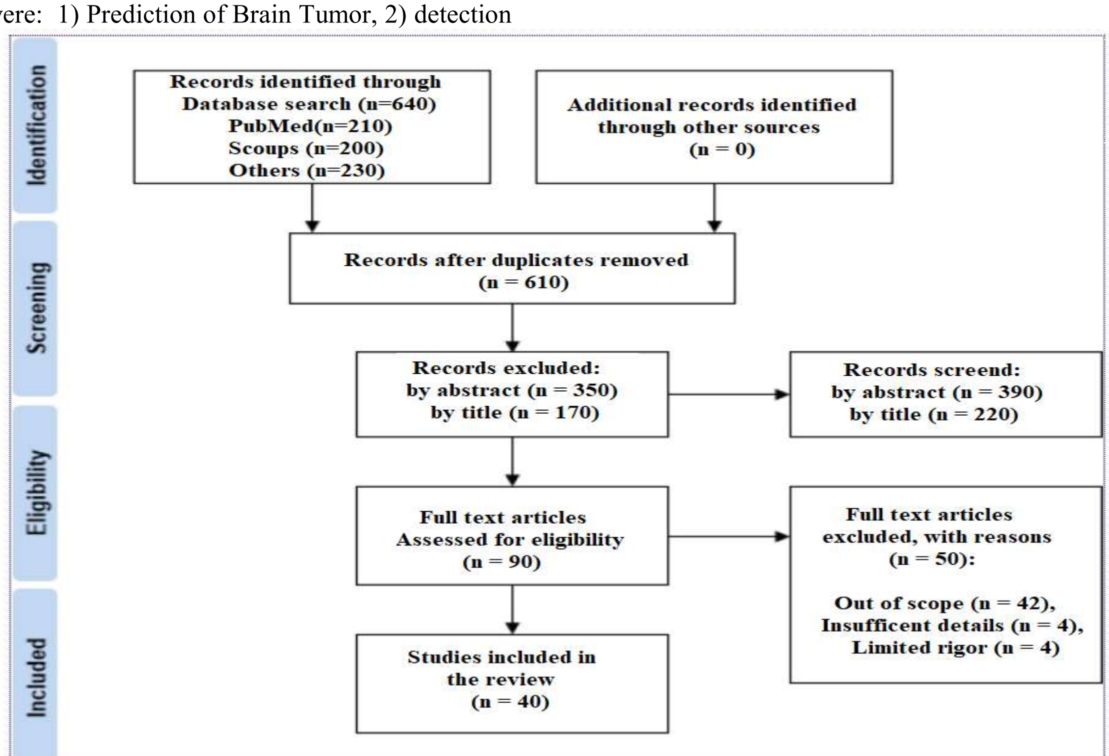

Figure1: PRISMA Flow Diagram (Identification Of Studies Via Databases)

Table 2. List Of Chosen Articles For The SLR With Their Areas Of Focus

#	Studies	Focus	#	Studies	Focus
1	[6]	Classification and detection of BT	**21**	[24]	BT detection
2	[18]	Improve the prediction BT	**22**	[25]	Detection and classification of BT
3	[19]	Prediction of BT	**23**	[28]	Detection and classification of BT
4	[1]	BT presence prediction	**24**	[29]	BT detection
5	[14]	Prediction of BT	**25**	[31]	BT detection
6	[15]	BT detection	**26**	[22]	Prediction of BT
7	[16]	Improve the prediction BT	**27**	[23]	Prediction of BT
8	[17]	Predict BT disease	**28**	[32]	Predict BT disease
9	[11]	Prediction of BT	**29**	[33]	Prediction of BT
10	[12]	CAD detection	**30**	[34]	BT detection
11	[13]	Detection and classification of brain tumors	**31**	[35]	BT Prediction
12	[2]	Methodology of detection of BT	**32**	[36]	BT Disease Diagnosis
13	[3]	Estimate a patient's overall survival	**33**	[37]	BT prediction
14	[4]	Predicting overall survival	**34**	[38]	BT prediction
15	[5]	BT diagnosis using segmentation	**35**	[21]	Predicting overall survival
16	[20]	Detection of BT	**36**	[26]	Prediction of BT
17	[7]	Detection of BT	**37**	[27]	Prediction of BT
18	[8]	BT diagnosis using segmentation	**38**	[30]	Detection and classification of brain tumors
19	[9]	Classification of BT	**39**	[39]	BT diagnosis using segmentation
20	[10]	Detection of BT	**40**	[40]	Classification of BT

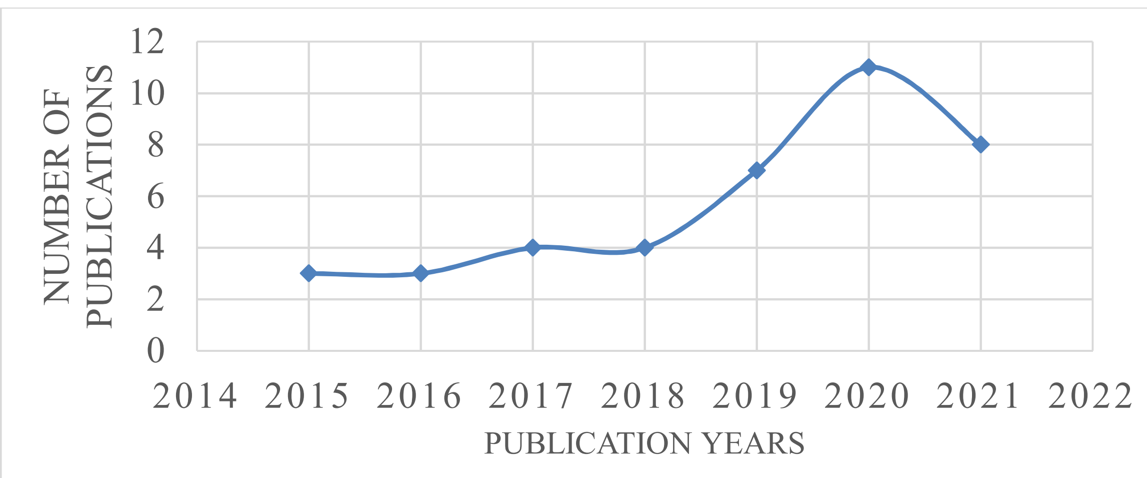

Figure 2: Publications Number On CVD Using DL And ML Methods Between 2015 And 2022

3.1 Algorithms

The SLR considered all stated procedures used in preceding studies. Table 3 and Figure 3 display a set of procedures used in the 40 articles and the amount of articles that embraced these techniques. The SLR shown that the top commonly employed ML procedures was Support Vector Machine (n=11, 50%), followed by K-Nearest Neighbors (KNN) (n=6, 27%), Decision Tree (DT) (n=3, 13%), and Random Forests (RF) (n=1, 5%). On the other hand, CNN showed most

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frequently used deep learning methods (n=21, 77%), followed by deep neural networks (n=6, 22%). 50% of the studies engaged multiple algorithms. One study engaged (KNN, DT, DNN, SVM, and CNN) supervised-learning DL and ML procedures and assessed their performance [39]. 97% of the articles used supervised-learning algorithms of classification to handle the attributes. Figure 3, shows that the methods SVM, ANN, KNN, CNN, DNN reserved their reputation. CNN has got more courtesy in this area than the others. From the years 2015 to 2021, at least one CNN article was published. Another frequently used method is Support Vector Machine (SVM).

Even though DNN have proved great analytical influence, they have documented few apps in CVDs field. The years (2017, 2019, and 2021) documented an increase in the use of assembling and boosting methods from (two to four) papers and a minor reduction to seven in the 2021. Furthermore, while no paper used the reinforcement-learning nor semi-supervised approaches, simply one paper employed unsupervised-learning procedure (K-Means) for BTs prediction, though the procedure achieved fine. RF and LR have recorded the lowest number of applications.

Table 3. ML Procedures Used In Previous Works

Algorithms used	Number of Research articles
Support Vector Machine (SVM)	11
K-Nearest Neighbors (KNN)	6
Decision-Tree (DT)	3
Random-Forest RF)	1
Neural-Network (ANN)	7
Logistic-Regression	1
Boosting & Ensembles	5
Convolutional Neural Network	21
Deep Neural Network	6

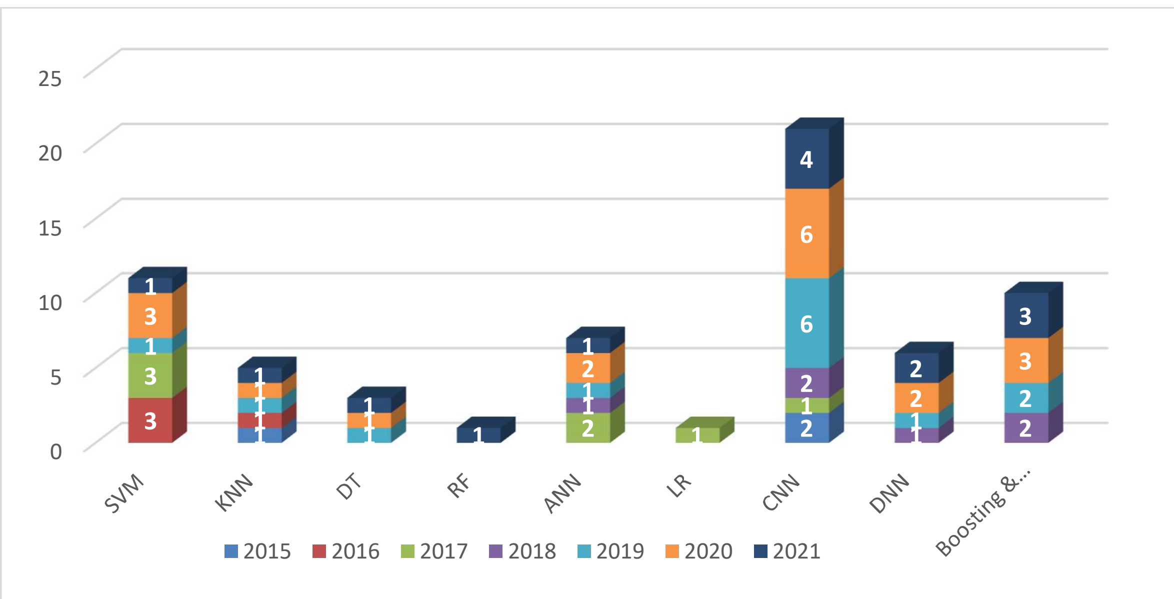

Figure 3. Illustrates The Yearly Usage Of Popular DL And ML Approaches For Prediction Of BT.

3.2 Algorithm Performance Metrics

One of the most crucial processes in the prediction process of ML is model assessment. Performance of an algorithm can be measured by means of a selection of metrics. Throughout the training process, measurements are frequently done using hidden examples. The algorithm metrics measurement performance applied in the included studies were "Precision, Specificity, Accuracy, Recall/Sensitivity, and F1-Score". The SLR discovered that the top used metrics assessment in prediction of BT are “Accuracy, followed by Recall/Sensitivity, F1-Score, Precision, and Specificity”. Table 4 shows that all 40 papers stated the accuracy rate used in these models for the prediction of BT. Figure 4 outlines the percentages of usage of the metrics in the examined articles. This study concentrated on analyzing algorithms performance of the used in the aforementioned studies. But, because it is not suitable to compare the efficiency of two procedures or systems directly if they were assessed on dissimilar datasets [9], the evaluation of the best-performing procedures is according to the same datasets that were used. Illustration on the top method used for assessment (i.e. Accuracy), the top performance algorithms were identified according to the mean values of the accuracy rate of the algorithms gotten from the 40 papers. For example study scope and health data vary greatly among BT prediction studies, a comparison can only be made after a consistent benchmark on the dataset and scope are established. Therefore, only studies that implemented multiple machine learning methods were carefully chosen for the comparison of the same data and BT prediction. The authors determined the algorithm with top performance for the same situation by relating the accuracy mean scores of the algorithms that employed the same datasets. Table 5 lists the algorithms used on the different datasets and the calculated mean scores with regard to Recall/sensitivity, specificity, precision, Accuracy, and F1-score. The current study draws on the calculated mean scores of the 40 articles to rank the most performing methods.

Thus, the higher the accuracy of an algorithm, the greater is the chance of creating perfect predictions. From Figure 5, BraTS 2015 Dataset is the most common one used and CNN model scored (96.25%) which is the highest accuracy rate prediction, after that DNN (95.307%), KNN (91.50%), ANN (88.43%), and SVM (74.24%). For the BraTS 2017 Dataset, the CNN (85.40%) models attained the top analytical accuracy percentage, as can be seen in Figure 6. For the BraTS 2018 Dataset, the CNN and DNN models achieved the top prediction accuracy percentage greater than 90%, as can be seen in Figure 7. In regards to the top performance, Figure 8 outlines that CNN has a better predictive accuracy percentage when related to the left over models for the Kaggle datasets. Figure 9, 10, and 11 show that the CNN model achieved the top accuracy percentage on the manually annotated images dataset (99.12%), webBrain dataset (99.75%), and WHO BT dataset (92.33%). Figure 12 shows the algorithm's top predictive accuracy percentage on Cancer-imaging-archive dataset is SVM (82%).

Table 4. ML Metrics Used In Previous Works

Metrics	No. of studies
Accuracy	42
F1-Score	9
Precision	9
Recall/Sensitivity	26
Specificity	16

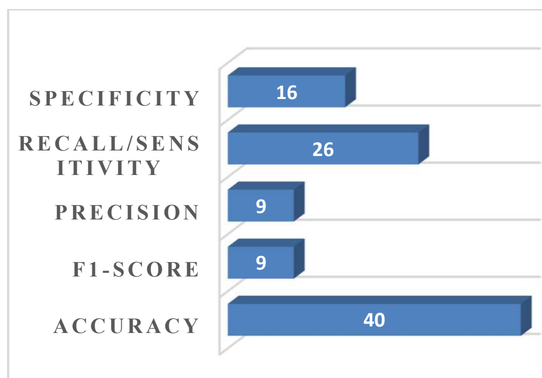

Figure 4. No. Of Algorithm Performance Metrics Used In Reviewed Articles.

Table 5. Performance Of Algorithms Based On Metrics Evaluation And Datasets

Dataset	Sample Size	Algorithms	ACC	F1-Score	Precision	Recall/Sensitivity	Specificity
BraTS 2015 Dataset	137	CNN	96.25	96.15	95.85	96.20	-
		KNN	91.50	-	-	-	91.50
		DNN	95.30	95.20	95.10	95.40	-
		ANN	88.43	-	-	-	-
		SVM	84.24	-	-	84.20	84.00
BraTS 2017 Dataset	163	KNN	66.70	-	-	66.60	66.40
		LOG REG	67.50	-		67.44	67.30
		SVM	80.42	-	-	80.20	80.07

		CNN	85.40	85.10	85.10	85.20	-
BraTS 2018 Dataset	233	CNN	91.87	87.10	87.00	87.97	95.13
		DNN	91.68	-	-	90.00	92.00
Flair dataset	500	SVM	69.99	-	-	-	-
Harvard Dataset	239	ANN	99.00	-	-	97.90	-
Kaggle Dataset	1000	DNN	93.50	88.80	88.60	93.35	98.08
		CNN	98.28	99.66	99.20	99.70	-
Manually annotated images	1667	CNN	99.12	-	-	-	-
		DT	84.69	-	-	-	-
WebBrain dataset	1000	DNN	97.40	97.30	97.10	97.55	-
		CNN	97.50	97.30	97.00	97.45	-
WHO dataset	254	CNN	92.33	-	-	-	-
		SVM	82.00	-	-	81.90	81.70
		ANN	80.40	-	-	80.65	80.50
Cancer Imaging Archive Dataset	48	SVM	82.00	-	-	81.90	81.70
		ANN	80.80	-	-	80.65	80.50

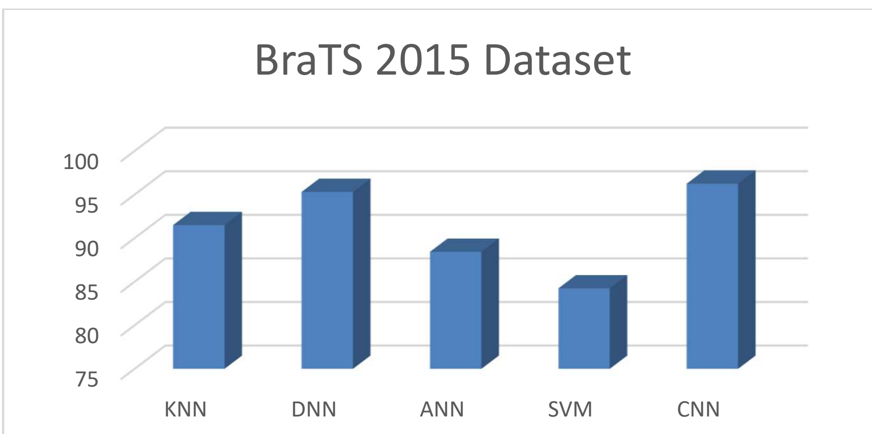

Figure 5. Best Performing Algorithm - Brats 2015 Dataset For BT Detection.

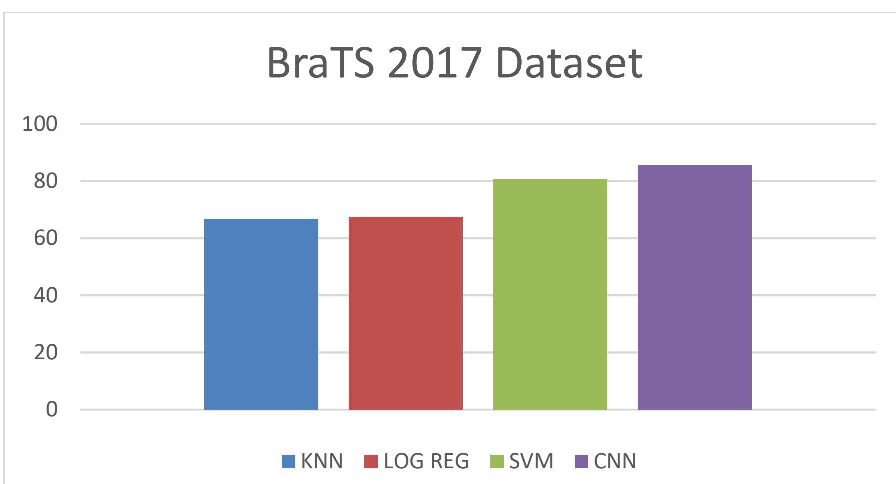

Figure 6. Best Performing Algorithm - Brats 2017 Dataset For BT Detection.

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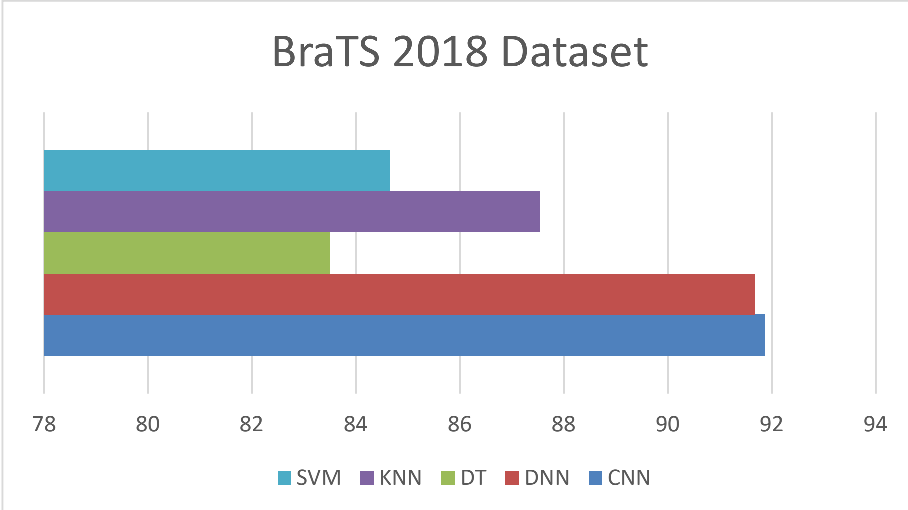

Figure 7. Best Performing Algorithm - Brats 2018 Dataset For BT Detection.

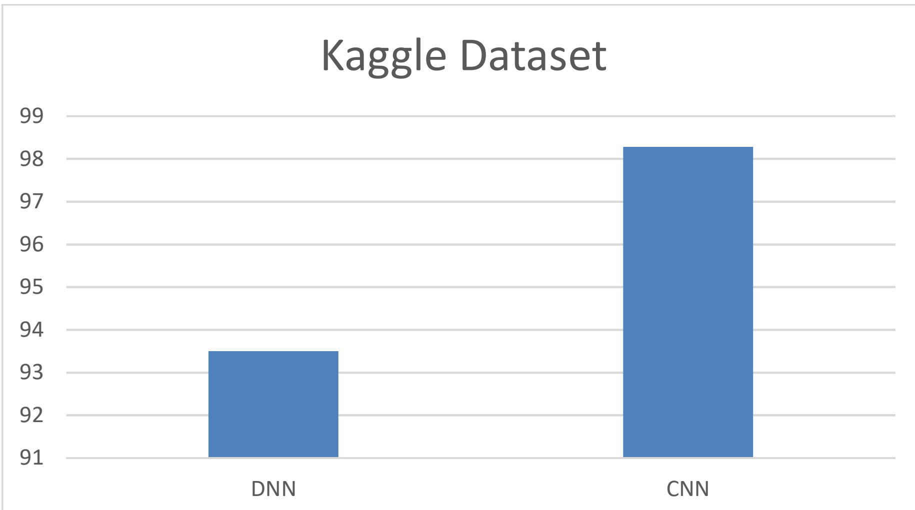

Figure 8. Best Performing Algorithm - Kaggle Dataset For BT Detection.

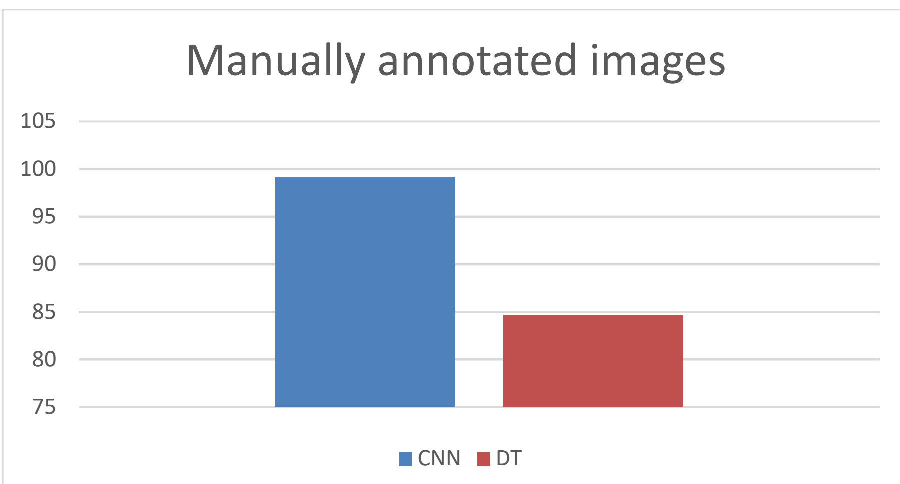

Figure 9. Best Performing Algorithm Manually Annotated Images For BT Detection.

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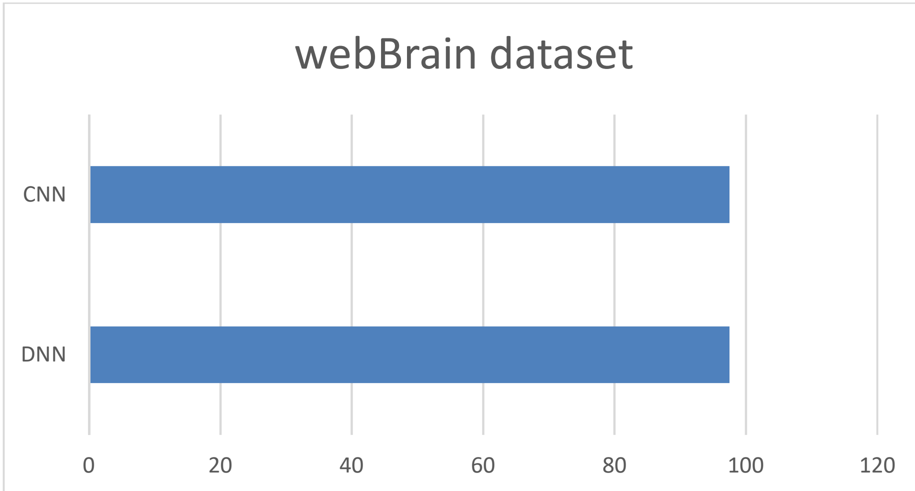

Figure 10. Best Performing Algorithm - Webbrain Dataset For BT Detection.

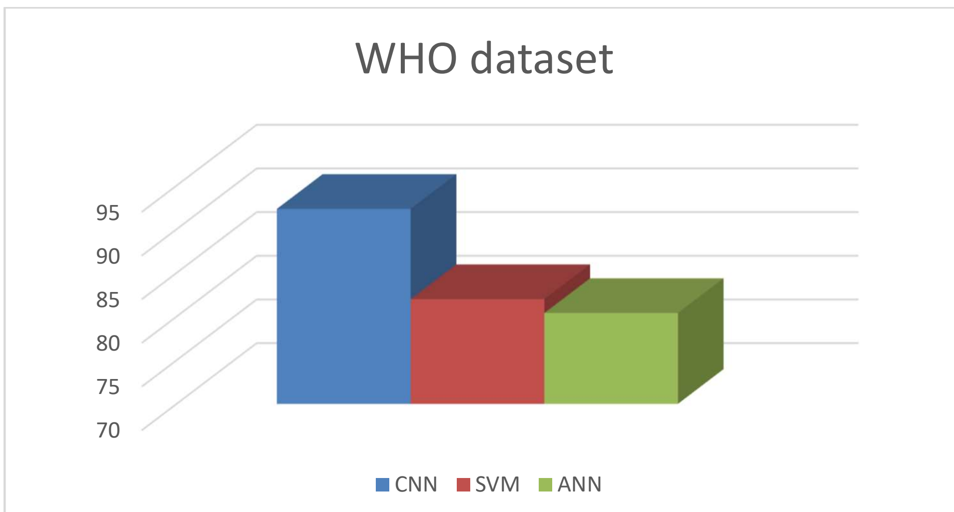

Figure 11. Best Performing Algorithm - WHO Dataset For BT Detection

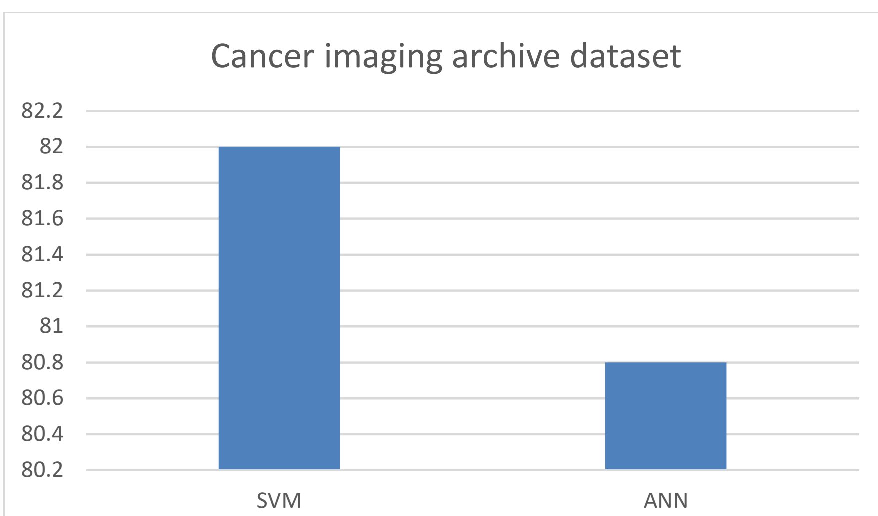

Figure 12. Top Performing Algorithm – Cancer Imaging Archive Dataset For Detection Of BT

Table 6: Metrics Performance For Primary Unpublished Datasets

Dataset	Sample Size	Algorithms	ACC	F1	Precision	Recall/Sensitivity	Specificity
CT scan centers	51	KNN	80.00	-	-	80.10	80.05
		SVM	79.40	-	-	79.25	79.10
Hilla Center for MRI	126	ANN	98.00	-	-	-	-
medical MR	200	ANN	92.14	-	-	89.00	94.00
MMRI dataset	220	SVM	99.70	-	-	-	-
multi-contrast MR scans	100	SVM	98.90	-	-	98.60	98.30
TCIA	252	CNN	95.00	94.60	94.30	94.70	-
Private 1	2556	KNN	97.30	-	-	97.35	97.10
		RF	91.50	-	-	91.45	91.30
		DT	90.44	-	-	90.40	90.04
Private 2	253	CNN	96.00	95.80	94.80	95.90	-
		DNN	89.00	88.70	88.50	88.80	-
Private 3	80	SVM	100.00	-	-	92.50	91.80

3.3 Datasets and Data Source

In DL and ML learning, datasets must be trained and validated to test models for accurate predictions of BT. In the studies reviewed in this study, two key data sets were detected: (1) open-access data sets and (2) un-published key data sets (as in Figure 13). The open access datasets engaged in those articles comprise the BraTS 2015, BraTS 2017, BraTS 2018, Figshare, Flair, Harvard, Kaggle, Manually annotated images, TCIA, WebBrain, Cancer imaging archive, and WHO data sets. Those data sets can be retrieved from the UCI depository or from Kaggle depository, or braintumors.org website. The open-access group comprises forty studies and 12 databases (Table VII), but some datasets were used in more than one study. For example, [15][18][22] used the BraTS 2015 BT data set collected from the UCI depository. The dataset contained 137 patients with Brain Tumors. According to the homepage of the dataset, most researchers utilize the MRI images of BT for the detection of whether a patient has brain Tumor or not. Out of the 40 papers used in this study, 13 papers applied the data set to study the BTs prediction. The second top prevalent data set employed in previous BT prediction studies was Figshare BT dataset. The dataset contains MRI images arranged into two groups: Normal, or abnormal. It categorizes patients into Health or not health. The data set was engaged in five articles and is accessible from the UCI Depository.

3.4 Software/Tools used for the *BT Prediction*

Deep and machine learning-based approaches are commonly employed for the prediction of Brain Tumor. Numerous tools and programming methods were employed for the development of the methods for the BT predictions. The reviewed studies applied different software for the analyses. These software/tools were classified into programming and data mining software (as in Figure 13). The programming language for deep and machine learning data analysis reported by the articles comprises Python programming platforms like R programming environment, Jupyter Notebook. WEKA, MATLAB, and Minitab are the commonly used data-mining apps. for BT predictions in these studies. Of the 40 papers reviewed, 57% (23 papers) stated the software usage. Out of these, 43% employed data-mining tools, however the remaining 57% used programming technologies. An evaluation and comparison of the various models presented the top accuracy of BT prediction with the programming languages. Numerous models, such as CNN, SVM, KNN, Log Reg, have been tested on the BraTS 2017 BT dataset, for example, using python and WEKA. The results showed that CNN, KNN, SVM, DNN, DT achieved accuracy rates of 92.15%, 87.55%, 84.65%, 91.68%, 83.5% with WEKA. Accuracy values obtained with Python were as follows: CNN (68.5), SVM (64.20), KNN (66.70), and LR (67.50).The assessment outcomes display that the recall, specificity, accuracy values of the various algorithms improved with WEKA.

Table 7: Tools used for DL and ML data analysis

Study	Software/Tool	Algorithms	Accuracy
[1]	R	KNN	96.15
[2]	R	CNN, DNN	96, 89
[3]	python	CNN, SVM	90.66, 84.60
[4]	Minitab	CNN	95.00
[5]	python	CNN	87.26
[6]	WEKA	DNN	98.02
[7]	R	ANN	99.00
[8]	python	ANN	92.14
[9]	R	ANN	98.00
[10]	Minitab	ANN	80.00
[11]	WEKA	SVM	98.90
[12]	R	SVM	100.00
[13]	python	SVM, ANN	82, 80.8
[14]	WEKA	KNN, SVM	80, 79.4
[15]	Minitab	CNN, KNN	96.25, 91.50
[16]	python	CNN, SVM, KNN, Log Reg	68.50, 64.20, 66.70, 67.50
[17]	WEKA	KNN, RF, DT	97.30, 91.50, 90.44
[18]	python	DNN	95.30
[19]	python	DNN	97.50
[20]	python	CNN, DNN	99.86, 88.98
[22]	python	ANN	88.43
[23]	WEKA	SVM	84.24
[24]	Python	CNN	97.50
[25]	python	CNN	94.68
[28]	WEKA	CNN	91.43
[29]	python	CNN	92.33
[31]	WEKA	CNN	94.82
[32]	WEKA	SVM	95.65
[21]	python	CNN	94.20
[26]	python	CNN	96.20
[27]	WEKA	CNN	99.61
[30]	Python	CNN	89.21
[33]	WEKA	SVM	69.99
[34]	R	CNN, DT	99.12, 84.69
[35]	WEKA	CNN	96.20
[36]	WEKA	SVM	99.70
[37]	Python	ANN	94.00
[38]	Python	CNN	96.7.00
[39]	WEKA	CNN, KNN, SVM, DNN, DT	92.15, 87.55, 84.65, 91.68, 83.50
[40]	WEKA	CNN	89.45

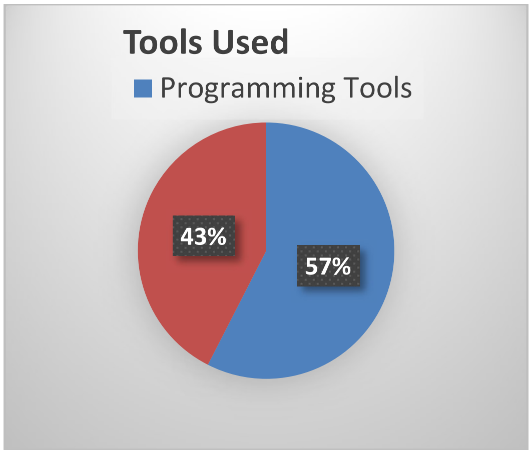

Figure 13: Distributions Analysis Of The Tools Used.

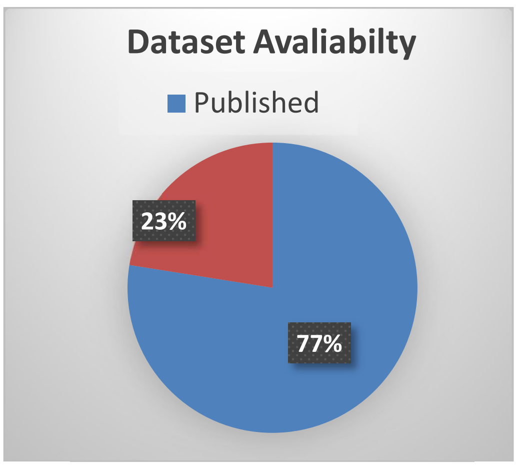

Figure 14: Distributions Of Data Set Used.

4. DISCUSSION

The current study has reviewed 40 articles that use DL and ML methods for the prediction of BT systematically. By following the questions of the review, it pursued to recognize the DL and ML methods employed for the predictions of BT, the dataset used, techniques of evaluation used, the software used and top-performing methods for the investigation. The consequence of this analysis high-lights the up-to-date DL and ML methods used in the BTs predicting gaps in future studies and their performances must be looked out. The outcomes display that preceding articles have concentrated on supervised ML detection based methods for observed methods. The review specified that Convolutional Neural Network, Deep Neural Network, SVMs, and KNN were the top used methods in predictions of BT articles, after that Artificial Neural Network, Ensemble algorithms, Decision Tree, and Logistic Regression. There are inadequate apps of sophisticated and innovative ensemble methods like XGBoost in spite of attaining attractiveness as an ensemble algorithm that has practically confirmed to be an exceedingly efficient method by achieving the top outcomes in many ML oppositions [17]. For the prediction of BT using DL and ML, no study applied, Adaboost, XGBoost, Bagging, Boosted Decision Tree, have got the least care

This SLR also concentrated on examining the performing of top DL and ML methods for prediction BT according to the stated assessment methods. The SLR recognized five measurement metrics for performance of model assessment. Those metrics are: “F1-Score, Accuracy, Specificity, Recall/Sensitivity and Precision”. This amount is considered sufficient for understanding and likening the study outcomes. As well as other metrics like AUC in upcoming articles is vital. AUC is considered an improved measure of classifiers than the accuracy because it’s un-biased environment on the testing data. In regards to the top-performing methods, the outcomes exhibited that hyper methods perform better than a standalone method for prediction of BT in regards to comparison of accuracy. This outcome opposes the results of [51] since the authors measured the performance of the methods by the AUC metric evaluation. Overall, the analysis prove that the DL and ML Accuracy methods are generally among (0.8 to 0.9+) in the prediction of BT. This specifies that the ability of the prediction of DL and ML methods are promising in BT, mainly with KNN, DNN, CNN, boosting, and SVM methods. Nonetheless, there may be operational obstructions to similar Accuracy of clinician level. As, there are inadequate circumstances for training and testing of the model. Consequently, additional articles likening DL and ML algorithms and human knowledge are compulsory. Furthermore, the ideal cutoff for accuracy still vague in the surveyed articles. As an example, an AUC score of 0.96 or greater is suggested, but this is not clear with Accuracy.

SLR likewise specified that out of the 40 articles, merely five engaged key medical datasets. It is recommended that data like this be employed in forthcoming articles to uphold the obligation to predict realistic BTs in local settings. This permits us to compare the consequences and sighted the real disadvantages or advantages of the suggested methods. The article likewise proposes that the publication of key clinical data sets and articles will certainly impact forthcoming improvements. The study did not find typical strategies for data splitting. Most articles engaged a cross validation approach and a (60:40, 70:30 or 80:20) dividing approach for the validation and training data sets. Moreover, since the size of most samples of datasets was pretty small, the combined consequences could be unfair. This SLR displays that top articles engaged data-mining tools fewer than programming language, containing Python, R, Google Collab, Jupyter Notebook, etc. Overall, the performance prediction in regards to the accuracy percentage of the methods (i.e., DT, LR, DT, ANN, RF, and SVM) achieved with the data-mining tools enhanced with Python and WEKA on the identical data set. Nonetheless, the run-time of a known method is likewise critical since if such a system is to be engaged in serious care divisions, a quick judgment needs to be completed.

4.1 Gaps and Forthcoming Research Directions

The novel study signifies the first SLR of DL and ML in BTs predictions. Assuming that disease prediction can aid pull attention to unnecessary involvements, it is vital to identify the up-to-date models of prediction, their performance of prediction, the environment of data sets, and the analysis of technologies. This review is important because it offers an opportunity to enhance these methods. According to the outcomes of the current study, forthcoming investigators must study these gaps:

- A lot more studies employing deep learning methods: similar to Xception, Res-Net, Inception, VGG, Mobile-Net networks are expected.
- Inadequate articles concentrated on RL and clustering methods.
- Further articles engaging ensemble methods, for instance the Support Vector Machine and Ensemble of Logistic Regression (ELR) are recommended for enhanced prediction.
- Approximately 50% of the involved articles were done in China or the USA. Studies from Asia, Americas (outside the USA) and Africa were inadequate. This may be partially because of the restricted availability of standard structured health data. More articles from the perspective of developing countries are mandatory.
- A main dependence on small sized sample-datasets in the involved articles. Since this may influence the enactment of DL and ML methods, articles with greater data sample sizes are mandatory.
- Involved articles hardly measured performance prediction in regards to AUC, which is recommended to be the top accuracy metric of measurement for classifiers. Forthcoming articles may emphasize on taking AUC as a metric measure of performance.

5. CONCLUSION

While predictions of BT using DL and ML apps are being commonly investigated, numerous concerns continue to be un-addressed. This research utilized the SLR method to examine up-to-date DL and ML methods used for BT predictions, assessment methods used and top-performing methods, the data set used, and tools used for the examination. This study has shown that a selection of methods can be smeared for predictions of BT. On the other hand, all methods are a member of a one class which is supervised-learning classification techniques; most articles use published datasets, while fewer studies use key clinical dataset. CNN, KNN, DNN, SVM, ANN, LR, DT, and boosting algorithms were found to be the best performing methods for prediction of BT; and programming analysis of data methods such as Python and R were found to yield greater predictive percentage than data-mining tools like MATLAB and MINTAB.

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