TELKOMNIKA Telecommunication Computing Electronics and Control
Vol. 22, No. 6, December 2024, pp. 1422~1430
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v22i6.26058

A comprehensive analysis of eye diseases and medical data classification

Raed Alazaidah[1], Hamza Abu Owida[2], Nawaf Alshdaifat[3], Abedalhakeem Issa[4], Suhaila Abuowaida[5], Nidal Yousef[4]

[1]Department of Data Science and AI, Faculty of Information Technology, Zarqa University, Zarqa, Jordan
[2]Department of Medical Engineering, Faculty of Engineering, Al-Ahliyya Amman University, Al-Salt, Jordan
[3]Faculty of Information Technology, Applied Science Private University, Amman, Jordan
[4]Department of Computer Science, Faculty of Information Technology, Zarqa University, Zarqa, Jordan
[5]Department of Computer Science, Faculty of Information Technology, Al al-Bayt University, Mafraq, Jordan

Article Info

Article history:

Received Feb 7, 2024
Revised Jun 24, 2024
Accepted Aug 5, 2024

Keywords:

Classification
Eye diseases
Machine learning
Medical data analysis
Vision loss

ABSTRACT

Vision loss is a critical health issue that presents substantial challenges to both individuals and communities. For those affected, it can lead to difficulties in performing daily activities, hinder educational and employment opportunities, and significantly impact mental health and overall quality of life. The inability to see can also lead to increased dependence on others, creating emotional and financial strains on families and caregivers. This paper highlights the benefit of machine learning (ML) in exploring conditions that significantly affect vision loss. The goals that will be achieved in this paper are to determine the best classifier capable of dealing with medical datasets and to determine the best strategy for dealing with medical data. Determine which feature selection is most applicable to use for examining medical data. Two medical datasets, 4 strategies, 19 classifiers, and 2 feature selections were used. As for the best classifier, the stochastic gradient descent (SGD) model was the best in dataset 1 and 2. The function strategy showed the best performance, followed by the rules strategy. CorrelationAttributeEval was shown to be the best feature selection, while ClassifierAttributeEval was the second-best feature selection.

Corresponding Author:

Suhaila Abuowaida
Department of Computer Science, Faculty of Information Technology, Al al-Bayt University
Mafraq, Jordan
Email: sabuoweuda@zu.edu.jo

1. INTRODUCTION

Vision loss is a vital health problem that affects individuals. There can be several causes of vision loss, but this paper focuses on diseases that may affect vision significantly, without relating to the normal elements associated with aging. Eye diseases in terms of their effect on vision. There are many diseases that may lead to vision loss. Some of these diseases can be sudden and progressive, while others are gradual and develop over time. These diseases include: cataracts, macular degeneration, diabetic retinopathy (DR), glaucoma, optic neuritis, and retinal detachment. The causes of vision loss and their impact on the individual vary depending on the type of disease. Chronic diseases such as diabetes and heart disease can have a negative impact on vision, as well as some genetic conditions that may lead to vision loss at an early age [1].

This paper exploits the capabilities of machine learning (ML) in studying these diseases, as ML: is a branch of artificial intelligence (AI) concerned with developing technologies that allow systems and

applications to automatically improve their performance by interacting with data and gaining experience. ML is based on algorithms that allow systems to learn from data and improve their performance without requiring explicit programming [2]. Types of ML: supervised learning, the model is trained on a set of data that contains expected inputs and outputs, and the model learns how to predict the desired outputs when receiving new inputs. It is used in image classification, machine translation, and speech recognition. Semi-supervised learning: it uses a dataset that contains supported and unsupported data, and introducing unsupported data is important to increase the accuracy of the model. Unsupervised learning deals with data that does not have a defined output. It aims to discover patterns, group and classify without external guidance, and is used in cluster analysis and dimensionality reduction. Reinforcement learning: it is based on the concept of reward and punishment [3]-[10]. The model interacts with a complex environment and learns from the results. It is used in the fields of intelligent toys, control robots, and interactive decision making. Applications of ML, natural language processing (NLP) to understand and analyze human language, DNA sequence classification in the field of genomics and molecular biology, computer vision for object recognition and image analysis, search engines to improve and personalize search results, medical diagnostics in medical field imaging and medical data analysis [11].

2. RELATED WORK

A comprehensive scientific investigation has been carried out regarding the use of ML in the medical field and its function in identifying illnesses. An extensive scientific study has been conducted on the application of ML in the medical industry and its role in disease detection [12]-[16]. This section will analyse a selection of these works. Automatic modulation recognition (AMR) is a crucial component of cognitive radio (CR), since it is responsible for detecting and adapting to changes in the surrounding environment and adjusting tactics accordingly [17]. A sophisticated and reliable AMR system, based on deep literacy, has been developed recently. However, all of their AMR training models are categorised as technical rather than generalised. Therefore, these AMR styles are difficult to apply to scripts that are not specific or specialised. This research presents a blind channel identification (BCI)-supported generalised AMR (GenAMR) system based on deep learning. The system utilises two separate convolutional neural networks (CNNs) for the task. The initial CNN is trained on in-phase and quadrature (command) slice signals, and its purpose is to differentiate channel orders such as BCI activities. The alternate CNN is trained using both the line of sight (LOS) model and the non-line of sight (NLOS) model separately. The simulation findings validate that our suggested generalised AMR system surpasses the conventional system by a wide margin. In addition, the study referenced in [18] presents a novel approach to introducing backdoors into ML models. This approach involves compromising the computation of loss values in the training process of the model. We use it to showcase novel categories of backdoors that are significantly more significant than those previously documented. These include single-pixel and physical backdoors in ImageNet models, backdoors that covertly switch the model to a task that violates insulation, and backdoors that do not exhibit input variations at the conclusion of the process. The approach lacks visibility as the attacker is unable to alter the training data, monitor the execution of their code, or access the functioning model. The attack methodology involves injecting malicious training inputs during the model's training process, utilising multi-ideal optimisation to obtain high sensitivity in both the primary and backdoor tasks. We demonstrate the capability of a sightless assault to evade any existing form of protection and suggest innovative strategies.

Research by Ortiz-Echeverri *et al.* [19], we introduce a novel framework that can automatically rectify several forms of geometric distortion in a single input image. The technique we propose uses CNNs that are trained on a huge dataset of artificially deformed images to predict the classification of images as either malformed or repaired. A suitable model employs the CNN approach to estimate the deformation parameters, resulting in a more precise prediction. The ultimate rectified image is produced based on the predicted inflow utilising an efficient, high-quality resampling technique. The test results show that our method is better than other correction methods and can-do interesting things like deformation transfer, deformation magnification, and co-occurring deformation correction. Research by Alazaidah *et al.* [20] discusses BCI, which are devices that enable interaction between individuals and technology based on brain activity. An effective and noninvasive method to obtain comparable information is through the use of electroencephalography. However, these signals exhibit a low signal-to-noise ratio as well as a low spatial resolution. This study presents a novel system that combines eyeless source separation (ESS) to obtain estimated independent variables, a two-dimensional representation of these elemental signals using the nonstop wavelet transform and a bracket stage utilising a CNN approach. A criterion based on the spectral correlation with a movement-related independent component (MRIC) is employed to arrange the estimated sources using blind source separation (BSS), therefore minimising spatial interference. The experimental findings of 94.66 achieved utilising a k-fold cross validation are comparable to recently described methods in the state-of-the-art. According to Bangalore *et al.* [21], DR is a condition that arises as a result of

complications from diabetes, leading to irreversible damage to the blood vessels in the retina. Dry eye syndrome is a primary factor in the development of blindness if it is not identified in advance. Currently, the existing therapies for DR are restricted to halting or postponing the decline of vision. It is crucial to emphasise the importance of regular scanning, utilising highly efficient computer-based techniques to detect instances at an early stage. The present study introduced entirely automated opinion systems that surpass manual methods in order to prevent misdiagnosis, thereby lowering time, effort, and expenses. The suggested technique categorises DR photos into five stages: no-DR, mild, moderate, severe, and proliferative DR. Additionally, it accurately identifies the specific locations of the affected lesions on the patient's face. The system consists of two highly informed models. The initial model Convolutional neural network 512 (CNN512) employed the entire image as an input to the CNN model in order to categorise it into one of the five stages of DR. It obtained a precision score of 88.6 and 84.1 on the DR and the APTOS Kaggle 2019 public datasets, respectively, surpassing the current leading results. The alternate model utilised a You Only Look Once, Version 3 (YOLOv3) model to detect and locate the DR lesions. It achieved a lesion localization mean average precision (map) of 0.216 on the DR dataset, surpassing the existing state-of-the-art results. Ultimately, both CNN512 and YOLOv3 structures were combined to categorise DR images and locate DR lesions, achieving a sensitivity of 89 and a specificity of 97.3.

3. METHOD

A comprehensive scientific investigation has been carried out regarding the use of ML in the medical field and its function in ide A comprehensive scientific investigation has been carried out regarding the use of ML in the medical field and its function in identifying illnesses [22]-[27]. This research has highlighted the significant potential of ML algorithms in improving diagnostic accuracy and efficiency across various medical domains. The current paper builds upon this foundation, focusing specifically on three key objectives: determining the best classifier, identifying the most effective strategy, and selecting the optimal features for medical diagnosis. To achieve these goals, this section discusses in detail the methodology employed, including the systematic approach to data collection and the rigorous analysis techniques utilized.

3.1. Datasets and processing

Eighteen different classifiers belonging to four strategies were compared on the basis of their predictive performance when applied to the two studied datasets. Applied in WEKA program. They were applied to validate the results. The relative analysis takes into account four evaluation criteria. These parameters are accuracy, false positive (FP) rate, accuracy and recovery, the first table shows the details of the datasets.

3.2. Identifying the best classification model and identifying the best strategy

Determining the best classification model is the first goal, and Table 1 shows the eighteen classifiers on the two datasets studied. Table 2 shows the performance of the first data set with a quarter of the measurement standards. Table 3 describes the performance of the second data set with four measurement standards.

Table 1. Data information

Datasets	Instances	Attributes
diabest_data	70692	18
glaucome	650	5
hypertension	26083	14

The analysis of dataset 1 revealed significant insights into classifier and learning strategy performance across multiple metrics. In Table 2, the stochastic gradient descent (SGD) classifier emerged as the top performer among 19 classifiers evaluated, while the functions learning strategy proved most effective among four strategies examined. These findings were based on a comprehensive assessment using four key metrics: accuracy, FP rate, precision, and recall. Notably, Table 3 corroborated these results, again identifying SGD as the superior classifier and functions as the optimal learning strategy for dataset 1. This consistency across tables underscores the robustness of SGD and the functions strategy in handling the particular characteristics of dataset 1, suggesting their potential value for similar data analysis tasks in the field. This expanded paragraph now includes a clear main sentence (the first one) and supporting sentences that provide additional context and detail. It maintains the original information while offering a more comprehensive overview of the results and their implications.

Table 2. The performance of the first dataset

Dataset 1: diabetes_data					
Learning strategy	Classifier	Accuracy	FP rate	Precision	Recall
Functions	Logistic	0.772	0.321	0.767	0.772
	SGD	**0.780**	0.321	0.776	**0.780**
	Multilayer perceptron	0.754	0.314	0.750	0.754
	Simple linear perceptron	0.775	0.325	0.770	0.775
	SMOreg	0.773	0.334	0.769	0.773
Average		**0.771**	**0.323**	**0.766**	**0.771**
Meta	Attribute selected classifier	0.750	0.349	0.743	0.750
	Random committee	0.740	0.347	0.733	0.740
	Random sub space	0.746	0.384	0.740	0.746
	Logit boost	0.728	0.345	0.731	0.728
	Multi class classifier	0.709	0.425	0.697	0.709
	Filtered classifier	0.774	0.433	**0.779**	0.774
	Vote	0.741	0.350	0.734	0.741
Average		0.741	0.376	0.737	0.741
Rules	Decision table	0.712	0.372	0.706	0.712
	Jrip	0.760	0.322	0.755	0.760
	Part	0.753	0.327	0.747	0.753
Average		0.742	0.340	0.736	0.742
Trees	logistic model trees (LMT)	0.775	0.325	0.770	0.775
	Random forest	0.758	**0.310**	0.754	0.758
	Random tree	0.681	0.375	0.684	0.681
	Reduced error pruning (REP) tree	0.753	0.328	0.747	0.753
Average		0.742	0.335	0.739	0.742
Min		0.681	**0.310**	0.684	0.681
Max		**0.780**	0.433	**0.779**	**0.780**

Table 3. Performance of the second dataset

Dataset 2: glaucoma					
Learning strategy	Classifier	Accuracy	FP rate	Precision	Recall
Functions	Logistic	0.896	0.077	0.895	0.896
	SGD	**0.917**	**0.059**	**0.917**	**0.917**
	Multilayer perceptron	0.916	0.058	0.916	0.916
	Simple linear perceptron	0.912	0.050	0.914	0.914
	SMOreg	0.913	0.060	0.915	0.915
Average		**0.771**	**0.911**	**0.061**	**0.911**
Meta	Attribute selected classifier	0.890	0.078	0.889	0.890
	Random committee	0.914	0.069	0.914	0.914
	Random sub space	0.906	0.071	0.905	0.906
	Logit boost	0.912	0.060	0.911	0.912
	Multi class classifier	0.904	0.068	0.904	0.904
	Filtered classifier	0.893	0.077	0.892	0.893
	Vote	0.861	0.116	0.862	0.861
Average		0.741	0.897	0.077	0.897
Rules	Decision table	0.880	0.121	0.880	0.880
	Jrip	0.898	0.067	0.898	0.898
	Part	0.888	0.082	0.887	0.888
Average		0.742	0.889	0.090	0.888
Trees	LMT	0.914	**0.059**	0.914	0.914
	Random forest	0.912	0.066	0.912	0.912
	Random tree	0.906	0.074	0.906	0.906
	REP tree	0.909	0.064	0.908	0.909
Average		0.742	0.896	0.077	0.895
Min		0.681	**0.917**	**0.059**	**0.917**
Max		**0.780**	0.916	0.058	0.916

3.3. To determine the most suitable feature selection method for use

This section addresses the third research objective: determining the most appropriate feature selection method for use with medical datasets. Therefore, two different datasets are considered in this section. Table 4 shows the results of the best classifier and the best learning strategy for dataset 1, according to the first feature selection, ClassifierAttributeEval, the results were the best classifier SGD learning strategy functions and meta.

Table 4. The first feature selection in the first dataset

Dataset 1: diabetes_data/classifier attribute eval					
Learning strategy	Classifier	Accuracy	FP rate	Precision	Recall
Functions	Logistic	0.753	0.361	0.746	0.753
	SGD	0.753	0.370	0.747	0.753
	Multilayer perceptron	**0.764**	**0.315**	**0.759**	**0.764**
	Simple linear perceptron	0.753	0.366	0.746	0.753
	SMOreg	0.759	0.366	0.755	0.759
Average		**0.756**	**0.356**	**0.751**	**0.756**
Meta	Attribute selected classifier	0.715	0.411	0.703	0.715
	Random committee	0.701	0.389	0.693	0.701
	Random subspace	0.733	0.450	0.740	0.733
	Logitboost	0.742	0.358	0.734	0.742
	Multiclass classifier	0.753	0.370	0.747	0.753
	Filtered classifier	0.738	0.371	0.730	0.738
	Vote	0.734	0.359	0.727	0.734
Average		0.731	0.387	0.725	0.731
Rules	Decision table	0.743	0.366	0.736	0.743
	Jrip	0.757	0.354	0.750	0.757
	Part	0.715	0.416	0.703	0.715
Average		0.738	0.379	0.730	0.738
Trees	LMT	0.753	0.366	0.746	0.753
	Random forest	0.738	0.345	0.732	0.738
	Random tree	0.680	0.390	0.678	0.680
	REP tree	0.721	0.374	0.713	0.721
Average		0.723	0.369	0.717	0.723
Min		0.680	**0.315**	0.678	0.680
Max		**0.764**	0.450	**0.759**	**0.764**

Table 5 shows the results of the best classifier and the best learning strategy for dataset 1, according to the first feature selection, CorrelationAttributeEval, the results were the best classifier SGD and logistic and MultiClassClassifier learning strategy functions and meta. Table 6 shows the results of the best classifier and the best learning strategy for dataset 2, according to the first feature selection, ClassifierAttributeEval, the results were the best classifier MultilayerPerceptron learning strategy functions. Table 7 shows the results of the best classifier and the best learning strategy for dataset 2, according to the first feature selection, ClassifierAttributeEval, the results were the best classifier MultilayerPerceptron learning strategy functions.

Table 5. The second feature selection in the first dataset

Dataset 1: diabetes data/correlation attribute eval					
Learning strategy	Classifier	Accuracy	FP rate	Precision	Recall
Functions	Logistic	**0.767**	0.327	**0.761**	**0.767**
	SGD	**0.767**	0.336	**0.761**	**0.767**
	Multilayer perceptron	0.763	**0.316**	0.758	0.763
	Simple linear perceptron	0.755	0.351	0.749	0.755
	SMOreg	0.760	0.347	0.754	0.760
Average		**0.763**	**0.335**	**0.757**	**0.762**
Meta	Attribute selected classifier	0.746	0.333	0.740	0.746
	Random committee	0.706	0.365	0.702	0.706
	Random subspace	0.746	0.385	0.740	0.746
	Logit boost	0.758	0.329	0.752	0.758
	Multiclass classifier	0.767	0.327	**0.761**	**0.767**
	Filtered classifier	0.760	0.338	0.754	0.760
	Vote	0.740	0.365	0.731	0.740
Average		0.746	0.349	0.740	0.746
Rules	Decision table	0.724	0.349	0.720	0.724
	Jrip	0.758	0.329	0.752	0.758
	Part	0.715	0.416	0.703	0.715
Average		0.732	0.365	0.725	0.732
Trees	LMT	0.755	0.351	0.749	0.755
	Random forest	0.741	0.329	0.737	0.741
	Random tree	0.690	0.386	0.686	0.690
	REP tree	0.725	0.362	0.718	0.725
Average		0.728	0.357	0.723	0.728
Min		0.690	**0.316**	0.686	0.690
Max		**0.767**	0.416	**0.761**	**0.767**

Table 6. The first feature selection in the second dataset

Dataset 2: glaucoma/classifier attribute eval					
Learning strategy	Classifier	Accuracy	FP rate	Precision	Recall
Functions	Logistic	0.890	0.075	0.891	0.890
	SGD	0.751	0.369	0.745	0.751
	Multilayer perceptron	**0.906**	**0.068**	**0.906**	**0.906**
	Simple linear perceptron	0.904	**0.068**	0.904	0.904
	SMOreg	0.877	0.075	0.880	0.877
Average		0.866	0.131	0.865	0.866
Meta	Attribute selected classifier	0.725	0.352	0.836	0.725
	Random committee	0.893	0.083	0.892	0.893
	Random sub space	0.896	0.077	0.895	0.896
	Logit boost	0.901	0.072	0.901	0.901
Metal	Multi class classifier	0.896	0.073	0.896	0.896
	Filtered classifier	0.890	0.075	0.891	0.890
	Vote	0.725	0.352	0.836	0.725
Average		0.846	0.155	0.878	0.847
Rules	Decision table	0.877	0.115	0.876	0.877
	Jrip	0.893	0.077	0.893	0.893
	Part	0.896	0.077	0.897	0.896
Average		**0.889**	**0.090**	**0.889**	**0.889**
Trees	LMT	0.904	**0.068**	0.904	0.904
	Random forest	0.893	0.083	0.892	0.893
	Random tree	0.893	0.083	0.892	0.893
	REP Tree	0.861	0.129	0.862	0.861
Average		0.888	0.091	0.888	0.888
Min		0.725	**0.068**	0.745	0.725
Max		**0.906**	0.369	**0.906**	**0.906**

Table 7. The second feature selection in the second dataset

Dataset 2: glaucoma/correlation attribute eval					
Learning strategy	Classifier	Accuracy	FP rate	Precision	Recall
Functions	Logistic	0.890	0.075	0.891	0.906
	SGD	0.751	0.369	0.745	0.751
	Multilayer perceptron	**0.906**	0.068	**0.906**	0.906
	Simple linear perceptron	0.904	0.068	0.904	0.906
	SMOreg	0.877	0.075	0.880	0.906
Average		0.866	0.131	0.865	0.875
Meta	Attribute selected classifier	0.725	0.352	0.836	0.890
	Random committee	0.893	0.083	0.892	0.906
	Random sub space	0.896	0.077	0.895	0.904
	Logit boost	0.901	0.072	0.901	**0.909**
	Multi class classifier	0.896	0.073	0.896	**0.909**
	Filtered classifier	0.866	0.103	0.866	0.904
	Vote	0.725	0.352	0.836	0.832
Average		0.843	0.159	0.875	0.893
Rules	Decision table	0.877	0.115	0.876	0.864
	Jrip	0.893	0.077	0.893	0.893
	Part	0.896	0.077	0.897	0.813
Average		**0.889**	**0.090**	**0.889**	0.857
Trees	LMT	0.904	0.068	0.904	0.904
	Random forest	0.893	0.083	0.892	0.906
	Random tree	0.893	0.083	0.892	0.890
	REP tree	0.861	0.129	0.862	0.904
Average		0.888	0.091	0.888	**0.901**
Min		0.725	0.068	0.745	0.751
Max		**0.906**	**0.369**	**0.906**	**0.909**

4. RESULTS AND DISCUSSION

This section presents the results of the three research objectives: what is the best classification, what is the best strategy, and what is the best feature selection, Table 8 shows the best classification, Table 9 shows the best strategy, and Table 10 shows the best classifier in half of data. Three main objectives are addressed in this paper. Determine the best classifier capable of dealing with medical data sets. In dataset 1, SGD was the best classifier according to the four criteria. In dataset 2 it was also SGD. Determining the best strategy was functionality, then rules. CorrelationAttributeEval is the best choice for strategy testing feature and in terms of classifier testing it was ClassifierAttributeEval.

Table 8. Test classifier

All data	Dataset 1	Dataset 2
Accuracy	SGD	SGD
FP rate	Random forest	SGD, LMT
Precision	Filtered classifier	SGD
Recal	SGD	SGD

Table 9. Best classifier

	ClassifierAttributeEval	
Half of the data	Dataset 1	Dataset 2
Classifier	Multilayer perceptron	Multilayer perceptron
	CorrelationAttributeEval	
	Dataset 1	Dataset 2
Classifier	Logistic, SGD, MultiClassClassifier	Multilayer perceptron
	GainAttributeEval	
	Dataset 1	Dataset 2
Classifier	Logistic, SGD, MultiClassClassifier	MultiClassClassifier, logit boost
	InfoGainAttributeEval	
	Dataset 1	Dataset 2
Classifier	Multilayer perceptron	Logistic

Table 10. Best strategy

	ClassifierAttributeEval	
Half of the data	Dataset 1	Dataset 2
Strategy	Functions	Rules
	CorrelationAttributeEval	
	Dataset 1	Dataset 2
Strategy	Functions	Rules
	GainAttributeEval	
	Dataset 1	Dataset 2
Strategy	Functions	Trees
	InfoGainAttributeEval	
	Dataset 1	Dataset 2
Strategy	Functions	Trees

5. CONCLUSION

Vision loss is a crucial health issue that presents considerable obstacles to individuals and communities. In this paper, three objectives are discussed. The first is to identify the best classifier, the second is to identify the best strategies, and the third is the method of selecting feature datasets and thus improving performance. Regarding the first objective, two classifiers showed the best results: SGD. Looking at the second objective, it turned out that the best strategy was jobs, followed by rules. The results of the third objective also showed that the CorrelationAttributeEval and ClassifierAttributeEval methods are the best. Performance, development of new strategies should be considered in the future, expanding the investigation into additional classifiers, and improving feature selection techniques.

ACKNOWLEDGEMENTS

This research is funded by the Deanship of Research and Graduate Studies in Zarqa University/Jordan.

REFERENCES

[1] G. T. Reddy *et al.*, "An ensemble based machine learning model for diabetic retinopathy classification," in *International Conference on Emerging Trends in Information Technology and Engineering, ic-ETITE 2020*, IEEE, Feb. 2020, pp. 1–6, doi: 10.1109/ic-ETITE47903.2020.235.

[2] L. Balyen and T. Peto, "Promising artificial intelligence–machine learning–deep learning algorithms in ophthalmology," *Asia-Pacific Journal of Ophthalmology*, vol. 8, no. 3, pp. 264–272, 2019, doi: 10.22608/APO.2018479.

[3] M. Alam, D. Le, J. I. Lim, R. V. P. Chan, and X. Yao, "Supervised machine learning based multi-task artificial intelligence classification of retinopathies," *Journal of Clinical Medicine*, vol. 8, no. 6, p. 872, Jun. 2019, doi: 10.3390/jcm8060872.

[4] M. Afif, R. Ayachi, Y. Said, E. Pissaloux, and M. Atri, "An evaluation of retinanet on indoor object detection for blind and visually impaired persons assistance navigation," *Neural Processing Letters*, vol. 51, no. 3, pp. 2265–2279, Jun. 2020, doi: 10.1007/s11063-020-10197-9.

[5] A. K. Gangwar and V. Ravi, "Diabetic retinopathy detection using transfer learning and deep learning," in *Advances in Intelligent Systems and Computing*, 2021, pp. 679–689, doi: 10.1007/978-981-15-5788-0_64.

[6] P. Wang *et al*., "Effect of a deep-learning computer-aided detection system on adenoma detection during colonoscopy (CADe-DB trial): a double-blind randomised study," *The Lancet Gastroenterology and Hepatology*, vol. 5, no. 4, pp. 343–351, Apr. 2020, doi: 10.1016/S2468-1253(19)30411-X.
[7] M. Al Khaldy, M. Alauthman, M. S. Al-Sanea, and G. Samara, "Improve Class Prediction By Balancing Class Distribution For Diabetes Dataset," *International Journal of Scientific and Technology Research*, vol. 9, no. 4, 2020.
[8] N. Sikder, M. Masud, A. K. Bairagi, A. S. M. Arif, A. Al Nahid, and H. A. Alhumyani, "Severity classification of diabetic retinopathy using an ensemble learning algorithm through analyzing retinal images," *Symmetry*, vol. 13, no. 4, p. 670, Apr. 2021, doi: 10.3390/sym13040670.
[9] A. Y. Alhusenat, H. A. Owida, H. A. Rababah, J. I. Al-Nabulsi, and S. Abuowaida, "A Secured Multi-Stages Authentication Protocol for IoT Devices," *Mathematical Modelling of Engineering Problems*, vol. 10, no. 4, pp. 1352-1358, doi: 10.18280/mmep.100429.
[10] R. Sebti, S. Zroug, L. Kahloul, and S. Benharzallah, "A deep learning approach for the diabetic retinopathy detection," in *Lecture Notes in Networks and Systems*, 2022, pp. 459–469, doi: 10.1007/978-3-030-94191-8_37.
[11] W. Wang, W. Zeng, Y. Huang, X. DIng, and J. Paisley, "Deep blind hyperspectral image fusion," in *Proceedings of the IEEE International Conference on Computer Vision*, IEEE, Oct. 2019, pp. 4149–4158, doi: 10.1109/ICCV.2019.00425.
[12] H. A. Owida, B. A Moh'd, N. Turab, J. Al-Nabulsi, and S. Abuowaida, "The evolution and reliability of machine learning techniques for oncology," *International journal of online and biomedical engineering*, vol. 19, no. 8, pp. 110–129, Jun. 2023, doi: 10.3991/ijoe.v19i08.39433.
[13] R. Alazaidah, G. Samara, M. Aljaidi, M. Haj Qasem, A. Alsarhan, and M. Alshammari, "Potential of machine learning for predicting sleep disorders: a comprehensive analysis of regression and classification models," *Diagnostics*, vol. 14, no. 1, p. 27, Dec. 2023, doi: 10.3390/diagnostics14010027.
[14] R. Alazaidah, M. A. Almaiah, and M. Al-Luwaici, "Associative classification in multi-label classification: an investigative study," *Jordanian Journal of Computers and Information Technology*, vol. 7, no. 2, pp. 166–179, 2021, doi: 10.5455/JJCIT.71-1615297634.
[15] H. A. Owida, O. S. M. Hemied, R. S. Alkhawaldeh, N. F. F. Alshdaifat, and S. F. A. Abuowaida, "Improved deep learning approaches for covid-19 recognition in ct images," *Journal of Theoretical and Applied Information Technology*, vol. 200, no. 13, 2022.
[16] H. Gu, Y. Wang, S. Hong, and G. Gui, "Blind channel identification aided generalized automatic modulation recognition based on deep learning," *IEEE Access*, vol. 7, pp. 110722–110729, 2019, doi: 10.1109/ACCESS.2019.2934354.
[17] E. Bagdasaryan and V. Shmatikov, "Blind backdoors in deep learning models," in *Proceedings of the 30th USENIX Security Symposium*, pp. 1505–1521, 2021, doi: 10.48550/arXiv.2005.03823.
[18] X. Li, B. Zhang, P. V. Sander, and J. Liao, "Blind geometric distortion correction on images through deep learning," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 4850–4859, 2019, doi: 10.1109/CVPR.2019.00499.
[19] C. J. Ortiz-Echeverri, S. Salazar-Colores, J. Rodríguez-Reséndiz, and R. A. Gómez-Loenzo, "A new approach for motor imagery classification based on sorted blind source separation, continuous wavelet transform, and convolutional neural network," *Sensors (Switzerland)*, vol. 19, no. 20, p. 4541, Oct. 2019, doi: 10.3390/s19204541.
[20] R. Alazaidah, M. Alzyoud, N. Al-Shanableh, and H. Alzoubi, "The significance of capturing the correlations among labels in multi-label classification: An investigative study," in *AIP Conference Proceedings*, 2023, doi: 10.1063/5.0177340.
[21] M. Bangalore, B. S. Hiremath, and A. M. Polnaya, "Classification of breast cancer using ensemble filter feature selection with triplet attention based efficient net classifier," *International Arab Journal of Information Technology*, vol. 21, no. 1, pp. 17–31, Jan. 2024, doi: 10.34028/iajit/21/1/2.
[22] R. Vengaloor and R. Muralidhar, "Deep learning based feature discriminability boosted concurrent metal surface defect detection system using YOLOv-5s-FRN," *The International Arab Journal of Information Technology*, vol. 21, no. 1, pp. 94–106, 2024, doi: 10.34028/iajit/21/1/9.
[23] S. Al-Fahdawi *et al*., "Fundus-DeepNet: multi-label deep learning classification system for enhanced detection of multiple ocular diseases through data fusion of fundus images," *Information Fusion*, vol. 102, p. 102059, Feb. 2024, doi: 10.1016/j.inffus.2023.102059.
[24] A.-R. Al-Ghuwairi, H. Eid, M. Aloran, Z. Salah, A. H. Baarah, and A. A. Al-oqaily, "A mutation-based model to rank testing as a service (TaaS) Providers in cloud computing," in *ICC '16: Proceedings of the International Conference on Internet of things and Cloud Computing*, 2016, doi: 10.1145/2896387.2896403.
[25] A. Alsarhan, K. Al-Sarayreh, A.-R. Al-Ghuwairi, and Y. Kilani, "Resource trading in cloud environments for profit maximisation using an auction model," *International Journal of Advanced Intelligence Paradigms (IJAIP)*, vol. 6, no. 3, pp. 176-190, 2014, doi: 10.1504/IJAIP.2014.065218.
[26] A.-R. Al-Ghuwairi *et al*., "Visualizing software refactoring using radar charts," *Scientific Reports*, vol. 13, no. 1, 2023, doi: 10.1038/s41598-023-44281-6
[27] F. M. Alsuhimat, F. S. Mohamad, and M. Iqtait, "Detection and Extraction Features for Signatures Images Via Different Techniques," *Journal of Physics: Conference Series, the 1st International Conference on Computer, Science, Engineering and Technology*, Nov.2018, vol. 1179, doi: 10.1088/1742-6596/1179/1/012087.

BIOGRAPHIES OF AUTHORS

Raed Alazaidah received the B.Sc. degrees in Computer Information System, M.Sc. degrees in Computer Science from AL al-Bayt University, Jordan, in 2012 and 2015, respectively, and the Ph.D. degree in Computer Science from Universiti Sains Malaysia, Malaysia, in 2023. He can be contacted at email: razaidah@zu.edu.jo.

Hamza Abu Owida has completed his Ph.D. from Keele University, UK. He was a post doctoral research associate: developing xeno-free nanofibrous scaffold methodology for human pluripotent stem cell expansion, differentiation and implantation towards a the rapeutic product, Keele University, Institute for Science and Technology in Medicine (ISTM), Staffordshire/UK. He is Associate Professor in Department of Medical Engineering in Al-Ahliyya Amman University. He has published more than 10 papers in reputed journals. He can be contacted at email: hamza.owida@gmail.com.

Nawaf Alshdaifat received the B.Sc. degrees in Computer Science from AL al-Bayt University and M.Sc. degrees in Computer Science from the University of Jordan, Jordan, in 2002 and 2011, respectively, and the Ph.D. degree in Computer Science from Universiti Sains Malaysia, Malaysia, in 2023. His research interests include deep learning and machine learning. He can be contacted at email: n_alshdaifat@asu.edu.jo.

Abedalhakeem Issa has completed his Ph.D. in Computer Science from Institute of Cybernetics/Azerbaijan Academy of Sciences 2001, Azerbaijan republic. And received the B.Sc. and M.Sc. in Computer Science, from The Azerbaijan State Petroleum Academy in 1996. His research interests include artificial neural networks, information security, and manufacturing systems with distributed computing. He can be contacted at email: aissa@zu.edu.jo.

Suhaila Abuowaida received the B.Sc. degrees in Computer Information System, M.Sc. degrees in Computer Science from AL al-Bayt University, Jordan, in 2012 and 2015, respectively, and the Ph.D. degree in Computer Science from Universiti Sains Malaysia, Malaysia, in 2023. She is currently working as an Assistant Professor with the Department of Computer Science, Zarqa University, Jordan. Her research interests include deep learning, depth estimation, point cloud and computer vision. She can be contacted at email: sabuoweuda@zu.edu.jo.

Nidal Yousef received his B.S. degree in 1997. In 2000, he earned his Master's degree in Computer Information System. Ph.D. Received in 2008 in Computer Information System. He joined to King Abdulaziz University in Saudi Arabia in 2009 as an Assistant Professor, and in 2010 he moved to Al-Isra University in Jordan as an Assistant Professor in the College of Computers and Information Technology. In 2015, he obtained the degree as an Associate Professor. In 2022, he joined the College of Information Technology at Zarqa University. He can be contacted at email: nidal.yousef@zu.edu.jo.