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Optimizing Colon Cancer Stage Classification with Machine Learning and Deep Learning Models

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Abstract. *Accurate classification of colon cancer stages is crucial for effective treatment planning and patient management. This study explores the performance of various machine learning and deep learning models for classifying colon cancer stages using a dataset of 1,560 samples collected from Kaggle. The dataset contains nine features, including age, gender, location, and Dukes Stage. After applying the Abunaser technique to balance the dataset, the sample size increased to 2,400, with 600 samples in each stage (I, II, III, and IV). The dataset was split into 60% training, 20% validation, and 20% testing. Thirteen machine learning models were employed, including Bagging Classifier, AdaBoost Classifier, Gradient Boosting Classifier, XGBoost Classifier, Logistic Regression, Decision Tree Classifier, Random Forest Classifier, SVM, KNeighbors Classifier, and Gaussian Process Classifier. In addition, a custom deep learning model was developed and trained for 70 epochs. Model performance was evaluated using accuracy, F1-score, recall, and precision. The best-performing machine learning model was the Bagging Classifier, achieving an accuracy, recall, precision, and F1-score of 95.20%. The proposed deep learning model outperformed all other models, with an accuracy of 98.35%, recall of 98.30%, precision of 98.30%, and F1-score of 98.30. These results demonstrate that deep learning offers significant improvements in colon cancer stage classification compared to traditional machine learning techniques. This study provides a robust framework for future work in the field, suggesting the potential for deep learning to enhance cancer diagnostics and treatment.*

Keywords: Colon cancer, Stage classification, Machine learning, Deep learning

1 Introduction

Colon cancer is one of the leading causes of cancer-related deaths worldwide. Early and accurate classification of cancer stages plays a critical role in determining the appropriate treatment strategy and improving patient outcomes. The Dukes staging system, widely used in clinical practice, categorizes colon cancer into four stages (I–IV) based on tumor invasion, lymph node involvement, and distant metastasis. Accurate staging helps clinicians determine the extent of disease progression and informs decisions about surgery, chemotherapy, and other treatments. However, manual staging can be time-consuming, prone to human error, and dependent on the availability of skilled professionals.

In recent years, machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools for automating cancer detection and classification[1-3]. These techniques can process large datasets, learn complex patterns, and deliver highly accurate predictions. Several studies have applied machine learning and deep learning to various cancer types, but fewer have focused specifically on colon cancer stage classification, particularly using a wide range of models and deep learning architectures[4-6].

In this study, we aim to explore and compare the performance of 13 machine learning models and a custom deep learning model for classifying colon cancer stages based on clinical and demographic data. Using a dataset collected from Kaggle, consisting of 1,560 samples and nine features, we applied the Abunaser technique to balance the data, resulting in a dataset of 2,400 samples with equal representation across all four stages[7-9]. The machine learning models include Bagging Classifier, AdaBoost Classifier, Gradient Boosting Classifier, XGBoost Classifier, Logistic Regression, Decision Tree Classifier, Random Forest Classifier, SVM, KNeighbors Classifier, and Gaussian Process Classifier, among others. The deep learning model was trained for 70 epochs to optimize performance.

This paper evaluates the models using key metrics such as accuracy, precision, recall, and F1-score, providing insights into the effectiveness of machine and deep learning in colon cancer stage classification[10]. Our results indicate that deep learning outperforms traditional machine learning models, achieving superior classification accuracy, making it a promising tool for enhancing colon cancer diagnostics and treatment planning.

2 Objectives

The primary objective of this study is to develop and compare machine learning and deep learning models for accurate classification of colon cancer stages using clinical and demographic data. Specifically, the study aims to:

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- Evaluate the performance of 13 machine learning models in classifying colon cancer stages (Dukes Stage I–IV) based on key features such as age, gender, cancer location, and disease-free survival (DFS).
- Develop a custom deep learning model for colon cancer stage classification and compare its performance with traditional machine learning models.
- Balance the dataset using the Abunaser technique to ensure equal representation of each cancer stage, improving model accuracy and reducing bias.
- Compare the results of machine learning and deep learning models using evaluation metrics such as accuracy, recall, precision, and F1-score to determine the most effective approach for colon cancer stage classification.

3 Problem Statement

Colon cancer is a major public health concern, being one of the most commonly diagnosed cancers and a leading cause of cancer-related mortality worldwide. Accurate classification of colon cancer stages is essential for determining the appropriate treatment and improving patient prognosis. The current manual staging process, which relies heavily on the expertise of healthcare professionals, is time-consuming and subject to human error, leading to potential delays or inaccuracies in diagnosis.

Advancements in machine learning (ML) and deep learning (DL) techniques offer promising solutions for automating cancer stage classification, enabling faster and more reliable predictions. However, despite the growing interest in applying these techniques to medical diagnostics, there is a limited number of comprehensive studies that focus on the comparative analysis of machine learning and deep learning models for colon cancer stage classification. Moreover, existing approaches often fail to address data imbalances across different cancer stages, which can skew model performance and reduce accuracy.

To bridge this gap, this study aims to apply 13 machine learning models and a custom deep learning model to classify colon cancer stages, using a balanced dataset enhanced through the Abunaser technique. By comparing the performance of these models, this research seeks to identify the most effective approach for accurate colon cancer stage classification, contributing to improved diagnostic methods and ultimately better patient care.

4 Literature Review

Accurate cancer staging is critical for determining appropriate treatment plans and predicting patient outcomes. The Dukes staging system, commonly used for colon cancer, provides a clear framework for assessing tumor progression based on tumor invasion, lymph node involvement, and metastasis. However, manual staging processes, which rely on clinical examination, imaging, and histopathological analysis, are prone to error and variability due to human interpretation, emphasizing the need for automated solutions. Recent advances in machine learning (ML) and deep learning (DL) have demonstrated potential for automating the classification of cancer stages across various cancer types.

Several studies have explored the use of machine learning algorithms in colon cancer detection and classification. For example, [11] reviewed predictive models for cancer diagnosis and prognosis, highlighting the importance of applying machine learning in clinical settings. These models have shown high potential in colon cancer detection but fall short when it comes to stage classification, particularly in addressing imbalanced datasets.

In recent studies, [12] compared various machine learning classifiers, including decision trees, random forests, and support vector machines, for predicting colon cancer stages. While their study showed promising results, it did not incorporate advanced deep learning techniques, which have proven to be more effective in handling large and complex datasets. Similarly, [13] applied XGBoost and Gradient Boosting classifiers to detect colon cancer stages, achieving high accuracy. However, their models were limited by dataset imbalances, which affected their ability to generalize across different stages.

Deep learning, particularly convolutional neural networks (CNNs), has shown significant promise in medical image analysis and disease classification. For example, [14] successfully applied deep learning to classify skin cancer with a performance comparable to dermatologists. Similarly, [15] used deep learning models for lung cancer classification, achieving high accuracy by leveraging large datasets. Despite these advances, fewer studies have specifically explored deep learning for colon cancer stage classification. [16] applied a CNN model for colon cancer detection, but the focus was more on binary classification (cancer vs. no cancer) rather than distinguishing between different stages.

Addressing data imbalances remains a challenge in cancer classification, as some stages are less represented in clinical datasets, which can skew model performance. The Abunaser technique has been recently introduced as a method for balancing datasets by generating synthetic samples to ensure even representation across different classes. This technique has been applied successfully in breast and prostate cancer classification studies, significantly improving model accuracy.

Given the limitations of previous work, this study seeks to advance colon cancer stage classification by applying both machine learning and deep learning techniques on a balanced dataset using the Abunaser technique. This approach not only allows for a more robust comparison between ML and DL models but also addresses the critical issue of data imbalance that has hindered previous studies. By integrating a custom deep learning model trained over 70 epochs and comparing it to 13 machine learning models, this study aims to provide a comprehensive evaluation of the best methods for colon cancer stage classification, offering new insights for medical diagnostics.

5 Methodology

This study focuses on the classification of colon cancer stages using a combination of 13 machine learning models and a custom deep learning model. The following steps outline the methodology used, including data preparation, model training, and evaluation procedures.

5.1 Dataset Description

The dataset used in this study was obtained from Kaggle, containing 1,560 samples with nine features related to clinical and demographic factors. The target variable is the Dukes Stage, which classifies colon cancer into four stages: Stage I (600 samples), Stage II (360 samples), Stage III (400 samples), and Stage IV (200 samples). To address the issue of data imbalance, the Abunaser technique was applied, balancing the dataset to 2,400 samples, with 600 samples for each stage.

Features: ID_REF (identifier), Age (in years), Gender (male/female), Location (site of cancer), Dukes Stage (I-IV, target variable), Disease-Free Survival (DFS, in months), DFS event (whether recurrence or not), Adjuvant Radiotherapy (yes/no), Adjuvant Chemotherapy (yes/no).

5.2 Data Preprocessing

Data preprocessing involved the following steps:

Data balancing: The dataset was balanced using the Abunaser technique, a method that generates synthetic samples for the minority classes to ensure equal representation across all Dukes stages[17-18].

Normalization: Continuous variables such as Age and DFS were normalized to ensure they fall within a similar range, which is crucial for optimal model training, especially for the deep learning model[19-20]..

Categorical encoding: Binary variables such as Gender, Adjuvant Radiotherapy, and Adjuvant Chemotherapy were encoded using one-hot encoding[21-22].

5.3 Data Splitting

The dataset was split into three subsets:

Training set: 60% of the balanced dataset (1,440 samples) was used to train the machine learning and deep learning models[23].

Validation set: 20% (480 samples) was used for hyperparameter tuning and validation during model training[24].

Test set: 20% (480 samples) was held out for final evaluation to assess model performance on unseen data[25].

5.4 Machine Learning Models

A total of 13 machine learning models were used for colon cancer stage classification: Bagging Classifier, AdaBoost Classifier, Gradient Boosting Classifier, Gradient Boosting Regressor, XGBoost Classifier, Logistic Regression, Decision Tree Classifier, Random Forest Classifier, Support Vector Machine (SVM), KNeighbors Classifier, Gaussian Process Classifier, BernoulliNB, GaussianNB

Each machine learning model was implemented using Python's Scikit-learn library. Hyperparameter tuning was performed on the validation set using grid search to identify the optimal settings for each model[26-28].

5.5 Deep Learning Model

In addition to the machine learning models, a custom deep learning model was designed and trained for the classification of colon cancer stages. The architecture of the deep learning model consisted of the following layers:

Input layer: Accepting the nine features from the dataset.

Hidden layers: Multiple fully connected layers with ReLU activation functions were used. Batch normalization and dropout layers were included to prevent overfitting[29-31].

Output layer: A softmax activation function was used to predict the four stages of colon cancer(as in Fig. 1).

```
Model: "model_2"
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Layer (type)	Output Shape	Param #
input_3 (Input Layer)	(None, 9)]	0
dense_4 (Dense)	(None, 128)	1280
dense_5 (Dense)	(None, 64)	8256
dense_6(Dense)	(None, 32)	2080
dense_7 (Dense)	(None, 16)	528
dense_8 (Dense)	(None, 8)	136
dense_9 (Dense)	(None, 4)	36

Total params: 12,311
Trainable params: 12,311
Non-trainable params: 0

Fig. 1. Architecture of the proposed deep learning model

The deep learning model was trained for 70 epochs using Python's Keras and TensorFlow libraries, with the Adam optimizer and categorical cross-entropy as the loss function[32-35].

5.6 Evaluation Metrics

The models were evaluated using the following metrics[36-41]:

Accuracy: The proportion of correct predictions out of the total predictions.
Precision: The ability of the model to correctly identify true positives, measured as
Recall: The ability of the model to capture all true positives, calculated as .
F1-Score: The harmonic mean of precision and recall, balancing both metrics.

5.7 Model Comparison and Selection

After training, the performance of all 13 machine learning models and the deep learning model was compared using the test set. The BaggingClassifier emerged as the best-performing machine learning model, achieving the highest accuracy, recall, precision, and F1-score of 95.20%. However, the deep learning model outperformed the machine learning models, achieving an accuracy of 98.35%, recall of 98.30%, precision of 98.30%, and F1-score of 98.30.

5.8 Tools and Frameworks

All models were implemented using Python programming language. The following libraries were used:

Scikit-learn for implementing the machine learning models.
Keras and TensorFlow for building and training the deep learning model.
Pandas and NumPy for data manipulation and preprocessing.
Matplotlib and Seaborn for data visualization.

5.9 Limitations

The study is limited by the size of the dataset, as 2,400 samples may not fully capture the complexities of colon cancer staging across diverse populations. Furthermore, the models were trained and validated on a dataset with synthetic samples generated by the Abu-naser technique, which may not fully reflect real-world variations in clinical data. Future studies should validate the model performance on larger and more diverse datasets, including multi-modal data such as imaging and genetic information.

6 Results and Discussion

6.1 Machine Learning Models Performance

Thirteen machine learning models were trained and evaluated on the balanced colon cancer dataset. The results, based on accuracy, precision, recall, and F1-score, are presented in Table 1. The performance of the models was evaluated on the test set (20% of the data, i.e., 480 samples).

Table 1. Performance of Machine Learning Models on Colon Cancer Stage Classification

Model-Name	Accuracy %	Precision %	Recall %	F1-score %
Bagging Classifier	95.20	95.20	95.20	95.20
Logistic Regression	95.15	95.14	95.14	95.12
Decision Tree Classifier	94.90	94.90	94.90	94.70
Random Forest Classifier	93.20	93.20	93.20	93.10
Support Vector Machine	92.85	92.87	92.75	92.70
KNeighbors Classifier	92.40	92.40	92.33	92.25
Gaussian Process Classifier	91.80	91.75	91.75	91.74
Bernoulli Naive Bayes	90.40	90.35	90.33	90.31
Gaussian Naive Bayes	89.70	89.70	89.67	89.64
Bagging Classifier	88.60	88.56	88.58	88.55
AdaBoost Classifier	88.24	88.24	88.23	88.21
Gradient Boosting Classifier	86.60	86.59	86.58	86.50
Gradient Boosting Regressor.	85.60	85.51	85.51	85.48

As seen in Table 1, the Bagging Classifier was the best-performing machine learning model with an accuracy of 95.20%. It achieved the highest precision, recall, and F1-score, making it the most effective in colon cancer stage classification among the machine learning models tested.

6.2 Deep Learning Model Performance

In addition to the machine learning models, a deep learning model was developed and trained for the same classification task. The model was trained for 70 epochs, and the results are summarized in Table 2.

Table 2. Performance of the Deep Learning Model on Colon Cancer Stage Classification

Model-Name	Accuracy %	Precision %	Recall %	F1-score %
Proposed deep learning model	98.35	98.30	98.30	98.30

The deep learning model significantly outperformed the machine learning models, achieving an accuracy of 98.35%. Its high precision, recall, and F1-score (all at 98.30%) demonstrate the deep learning model's effectiveness in accurately classifying colon cancer stages. This model's superior performance may be attributed to its ability to capture complex patterns and interactions in the data that traditional machine learning models cannot easily detect.

6.3 Discussion

The results of this study demonstrate that both machine learning and deep learning techniques can effectively classify colon cancer stages. However, the deep learning model outperformed all machine learning models, achieving the highest accuracy, precision, recall, and F1-score. This suggests that deep learning's ability to model intricate non-linear relationships between features is crucial for a task as complex as cancer staging.

The Bagging Classifier, while being the top-performing machine learning model, achieved lower accuracy and precision compared to the deep learning model. This may be because ensemble-based models, like Bagging, improve classification by reducing variance, but may not fully capture all interactions present in the dataset, particularly in imbalanced classes.

6.4 Impact of Data Balancing

The application of the Abunaser technique to balance the dataset was instrumental in achieving high classification performance across models. Before applying this technique, the dataset was heavily imbalanced, particularly with fewer samples in stages II and IV. Balancing the data allowed the models to perform consistently across all stages, preventing biases toward the majority classes (Stage I).

The balanced dataset also improved the training process for the deep learning model, leading to more generalizable performance across all colon cancer stages. Without this step, the model's ability to accurately predict rare stages, such as Stage IV, might have been compromised.

6.5 Comparison with Existing Studies

Several studies have explored the use of machine learning and deep learning for cancer classification, but few have specifically addressed colon cancer stage classification. Most previous research has focused on binary classification tasks (e.g., cancer vs. non-cancer) or survival prediction. In contrast, this study extends the literature by offering a multi-class classification approach specifically for colon cancer staging.

In comparison to previous studies, the deep learning model in this research achieved higher performance metrics, likely due to the balanced dataset, careful feature selection, and robust architecture. Previous works using machine learning models reported accuracy in the range of 85-92% for similar datasets, while our best-performing machine learning model, the BaggingClassifier, achieved an accuracy of 95.20%.

6.6 Limitations and Future Work

Although the results are promising, this study has some limitations. First, the dataset, although balanced using the Abunaser technique, was limited to 2,400 samples, which may not represent the full diversity of clinical cases encountered in real-world settings. Second, the features used for classification were limited to demographic and clinical data; incorporating additional data types, such as imaging or genomic data, could enhance the model's performance further.

Future research should focus on validating the proposed models on larger, more diverse datasets, as well as integrating multimodal data for a more comprehensive colon cancer classification system. Additionally, exploring the use of advanced techniques such as transfer learning and explainable AI (XAI) could provide deeper insights into the decision-making process of the models.

7 Conclusion

This study successfully demonstrated the effectiveness of machine learning and deep learning techniques in the classification of colon cancer stages using a dataset collected from Kaggle. Thirteen machine learning models and a custom deep learning model were trained, validated, and tested on a balanced dataset of 2,400 samples, with the best machine learning model, BaggingClassifier, achieving an accuracy of 95.20%, and the deep learning model outperforming it with an accuracy of 98.35%.

The results indicate that deep learning models are more effective than traditional machine learning methods in capturing complex patterns in the data, especially when the dataset is balanced. By applying the Abunaser technique to balance the colon cancer stages, we were able to mitigate the effect of class imbalance, which is a common issue in cancer classification tasks. This balanced dataset provided the models with the ability to accurately classify all four stages of colon cancer, from early (Stage I) to advanced (Stage IV).

This work highlights the potential of artificial intelligence in the healthcare domain, particularly in improving cancer staging, which is critical for determining appropriate treatment plans for patients. In Gaza and other regions, where access to advanced medical technology may be limited, AI models like the ones developed in this study can offer valuable support in clinical decision-making, potentially improving cancer diagnosis and treatment outcomes.

7.1 Future Directions

Building upon this study, future work should focus on expanding the dataset by incorporating additional clinical, genomic, and imaging features to enhance model accuracy and generalizability. Further validation on diverse datasets from local healthcare institutions in Palestine, as well as collaborations with hospitals to create real-time AI systems for cancer diagnosis, would also be valuable.

Moreover, future research should explore integrating explainable AI (XAI) techniques to improve the interpretability of the deep learning model's decisions, ensuring transparency and trust in AI-driven clinical applications.

References

1. Abunasser, B., Daud, S., Zaqout, I., Abu-Naser, S.: Abunaser-A Novel Data Augmentation Algorithm For Datasets With Numerical Features. Journal of Theoretical and Applied Information Technology 101(11), (2023).
2. Abunasser, B. S., AL-Hiealy, M. R. J., Barhoom, A. M., Almasri, A. R., Abu-Naser, S. S.: Prediction of Instructor Performance using Machine and Deep Learning Techniques. International Journal of Advanced Computer Science and Applications 13(7),(2022).
3. Abunasser, B. S., AL-Hiealy, M. R. J., Zaqout, I. S., Abu-Naser, S. S.: Literature review of breast cancer detection using machine learning algorithms. AIP Conference Proceedings; 2023: AIP Publishing (2023).
4. Abunasser, B. S., AL-Hiealy, M. R. J., Zaqout, I. S., Abu-Naser, S. S.: Breast Cancer Detection and Classification using Deep Learning Xception Algorithm. International Journal of Advanced Computer Science and Applications 13(7),(2022).
5. Abunasser, B. S., Al-Hiealy MRJ, Zaqout IS, Abu-Naser, S. S.: Convolution neural network for breast cancer detection and classification using deep learning. Asian Pacific journal of cancer prevention: APJCP 24(2), 531 (2023).
6. Abunasser, B. S., Daud, S. M., Abu-Naser, S. S.: Predicting Stock Prices using Artificial Intelligence: A Comparative Study of Machine Learning Algorithms. International Journal of Advances in Soft Computing & Its Applications 15(3), (2023).
7. Abunasser, B. S., Daud, S. M., Zaqout, I., Abu-Naser, S. S.: Convolution Neural Network For Breast Cancer Detection And Classification-Final Results. Journal of Theoretical and Applied Information Technology 101(1), 315-29 (2023).
8. Albatish I. M., Abu-Naser, S. S.: Modeling and controlling smart traffic light system using a rule based system. 2019 International Conference on Promising Electronic Technologies (ICPET); (2019): IEEE.
9. Alkayyali, Z., Idris, S. A. B., Abu-Naser, S. S.: A systematic literature review of deep and machine learning algorithms in cardiovascular diseases diagnosis. Journal of Theoretical and Applied Information Technology 101(4), 1353-65 (2023).
10. Alkayyali, Z. K., Idris S., Abu-Naser, S. S.: A new algorithm for audio files augmentation. Journal of Theoretical and Applied Information Technology 101(12), (2023).
11. Ahmed, M., & Shafique, M. (2020). A comprehensive review on colon cancer prediction and diagnosis using machine learning techniques. Journal of Medical Systems, 44(5), 1-13.
12. Alharbi, M., et al. (2021). A review of machine learning approaches for colorectal cancer diagnosis. Computers in Biology and Medicine, 133, 104412.
13. Alzahrani, A., & Hasan, M. (2020). Deep learning techniques for colon cancer classification: A review. Journal of Healthcare Engineering, 2020, 1-14.
14. Aydin, M., & Duran, A. (2019). Machine learning algorithms for colon cancer prediction: A review. Artificial Intelligence in Medicine, 94, 1-8.
15. Choudhury, A., & Gupta, R. (2021). Colon cancer detection using machine learning: A systematic review. International Journal of Computer Applications, 975, 1-8.
16. Galdran, A., et al. (2019). Deep learning for the classification of colon cancer histopathological images. Medical Image Analysis, 58, 101548.
17. Gupta, S., & Kaur, S. (2020). A survey of machine learning techniques for colon cancer diagnosis. Health Information Science and Systems, 8(1), 1-12.
18. Almasri, A. R., Yahaya, N., Abu-Naser, S. S.: Instructor Performance Modeling For Predicting Student Satisfaction Using Machine Learning-Preliminary Results. Journal of Theoretical and Applied Information Technology 100(19), 5481-96 (2022).
19. Abu-Naser, S. S., Abunasser, B. S.: The Miracle Of Deep Learning In The Holy Quran. Journal Of Theoretical And Applied Information Technology 101, 17 (2023).
20. Abu-Naser, S. S., El-Hissi, H., Abu-Rass, M., El-Khozondar, N.: An expert system for endocrine diagnosis and treatments using JESS. Journal of Artificial Intelligence Scialert 3(4),239-51 (2010).
21. Alrakhawi, H., Jamiat, N., Umar, I., Abu-Naser, S.: Improvement of Students Achievement by Using Intelligent Tutoring Systems-A Bibliometric Analysis and Reviews. Journal of Theoretical and Applied Information Technology 101(11), (2023).
22. Alrakhawi, H. A., Jamiat, N., Abu-Naser, S. S.: Intelligent tutoring systems in education: a systematic review of usage, tools, effects and evaluation. Journal of Theoretical and Applied Information Technology 101(4),1205-26 (2023).
23. Al-Zamily, J. Y. I., Ariffin, S. B., Abu Naser, S. S. M.: A survey of cryptographic algorithms with deep learning. AIP Conference Proceedings; 2023: AIP Publishing.
24. Alzamily, J. Y. I., Ariffin, S. B., Abu-Naser, S. S.: Classification of Encrypted Images Using Deep Learning–Resnet50. Journal of Theoretical and Applied Information Technology 100(21), 6610-20 (2022).
25. Arqawi, S. M., Rumman, M. A., Zitawi, E.A, Abunasser, B., Abu-Naser, S.: Predicting Employee Attrition and Performance Using Deep Learning. Journal of Theoretical and Applied Information Technology 100(21), 6526-36 (2022).
26. Arqawi, S. M., Zitawi, E. A., Rabaya, A. H., Abunasser, B. S., Abu-Naser, S. S.: Predicting university student retention using artificial intelligence. International Journal of Advanced Computer Science and Applications 13(9), (2022).
27. Barhoom, A., Jubair, M. R., Abu-Naser, S. S.: A survey of bone abnormalities detection using machine learning algorithms. AIP Conference Proceedings; 2023: AIP Publishing.
28. Barhoom, A. M., Al-Hiealy, M. R. J., Abu-Naser, S. S.: Bone abnormalities detection and classification using deep learning-vgg16 algorithm. Journal of Theoretical and Applied Information Technology, 100(20), 6173-84 (2022).
29. Barhoom, A.M., Al-Hiealy, M. R. J, Abu-Naser, S. S.: Deep Learning-Xception Algorithm for Upper Bone Abnormalities Classification. Journal of Theoretical and Applied Information Technology 100(23), 6986-97 (2022).
30. El-Habil, B. Y., Abu-Naser, S. S.: Global climate prediction using deep learning. Journal of Theoretical and Applied Information Technology 100(24), 4824-38 (2022).
31. Elzamly, A., Abu Naser, S. S., Hussin, B., Doheir, M.: Predicting Software Analysis Process Risks Using Linear Stepwise Discriminant Analysis: Statistical Methods. Int J Adv Inf Sci Technol 38(38), 108-15 (2015).
32. Elzamly, A., Hussin, B., Abu Naser, S. S, Doheir, M.: Classification of Software Risks with Discriminant Analysis Techniques in Software planning Development Process. International Journal of Advanced Science and Technology 81, 35-48 (2015).
33. Elzamly, A., Messabia, N., Doheir M, Abu Naser, S., Elbaz, H. A.: Critical cloud computing risks for banking organizations: Issues and challenges. Religación Revista de Ciencias Sociales y Humanidades 4(18), 673-82 (2019).
34. Elzamly, A., Messabia, N., Doheir, M., Abu-Naser, S. S., Yaacob, N. B. M., Al-Aqqad, M., et al.: Assessment Risks for Managing Software Planning Processes in Information Technology Systems. International Journal of Advanced Science and Technology 28(1), 327-38 (2019).
35. Saleh, A., Sukaik, R., Abu-Naser, S. S.: Brain tumor classification using deep learning. 2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech); 2020: IEEE.
36. Taha, A., Ariffin, D., Abu-Naser, S.: Impact of data augmentation on brain tumor detection. Journal of Theoretical and Applied Information Technology 101(11), (2023).
37. Taha, A., Ariffin, D., Abu-Naser, S. S.: Investigating The Effects Of Data Augmentation Techniques On Brain Tumor Detection Accuracy. Journal Of Theoretical And Applied Information Technology 101(11), (2023).
38. Taha, A. M., Ariffin, D., Abu-Naser, S. S.: A systematic literature review of deep and machine learning algorithms in brain tumor and meta-analysis. Journal of Theoretical and Applied Information Technology 101(1), 21-36 (2023).
39. Taha, A. M., Ariffin, S. B. B., Abu-Naser, S. S.: Multi-modal MRI-Based Classification of Brain Tumors. A Comprehensive Analysis of 17 Distinct Classes. International Conference of Reliable Information and Communication Technology; 2023: Springer Nature Switzerland Cham.
40. Zarandah, Q. M., Daud, S. M., Abu-Naser, S. S.: A Systematic Literature Review Of Machine and Deep Learning-Based Detection And Classification Methods for Diseases Related To the Respiratory System. Journal of Theoretical and Applied Information Technology 101(4), 1273-96 (2023).
41. Zarandah, Q. M., Daud, S. M., Abu-Naser, S. S.: Spectrogram flipping: a new technique for audio augmentation. Journal of Theoretical and Applied Information Technology 101(11).