

Analysis of Multi-type Barcode Images Using Hybrid CNN-Transformer Model for Water Quality Classification

Birkan Büyükarıkan^{1*}, Zehra Gök²

Abstract: Water quality is a critical factor for both human health and aquatic ecosystems. An inaccurate assessment of water quality can have serious consequences, including risks to drinking water supplies and adverse effects on aquatic life. Therefore, there is growing demand for rapid, reliable methods to estimate water quality. In recent years, the application of deep learning (DL)-based methods for assessing water quality has increased significantly. DL methods achieve high classification performance by autonomously learning relationships within complex water quality datasets. This study aims to classify two-dimensional barcode-based visual representations of water quality using advanced DL architectures. The study used a tabular water-quality dataset comprising physicochemical parameters, which were subsequently transformed into QR, Aztec, and Data Matrix code images. These barcode datasets were initially evaluated using transfer learning with the MobileNet, MobileNetV2, and MobileNetV3Small Convolutional Neural Network (CNN) architectures, with a 5-fold cross-validation approach. Subsequently, the MobileNetV3Small model, which achieved the highest classification performance, served as the backbone of the CNN-Transformer architecture, enabling image classification with this proposed model. Based on the experimental results, the highest average performance was achieved on the Aztec code dataset. Specifically, the MobileNetV3Small model attained an accuracy of $91.95 \pm 1.19\%$, whereas the MobileNetV3Small-Transformer model reached $97.72 \pm 2.19\%$. Additionally, the proposed MobileNetV3Small-Transformer model yielded accuracy rates of $92.65 \pm 5.88\%$ on the QR code dataset and $90.44 \pm 7.76\%$ on the Data Matrix code dataset. This approach presents an alternative methodology for evaluating tabular data through visual representations and DL techniques in the field of environmental data analytics.

Keywords: Water quality, tabular data, barcode images, convolutional neural networks, transformer architecture

Su Kalitesinin Sınıflandırılması için Hibrit CNN-Transformer Modeli ile Çok Türlü Barkod Görüntülerinin Analizi

Özet: Su kalitesi, insan sağlığı ve suda bulunan canlıların yaşamları için oldukça önemli bir faktördür. Su kalitesinin yanlış değerlendirilmesi, su temini ve su ekosistemleri bakımından olumsuz sonuçlar oluşturabilmektedir. Bu nedenle su kalitesinin doğru ve hızlı biçimde belirlenmesi önemli bir gerekliliktir. Son yıllarda, su kalitesinin değerlendirilmesi amacıyla derin öğrenme (DL) tabanlı yöntemlerin kullanımı giderek artmıştır. DL yöntemleri, karmaşık su kalitesi verileri arasındaki ilişkileri otomatik olarak öğrenebilme yetenekleri sayesinde, yüksek sınıflandırma performansı sunmaktadır. Bu bağlamda, çalışmanın amacı, su kalitesine ait iki boyutlu barkod tabanlı görsel temsillerin DL mimarileriyle sınıflandırılmasıdır. Çalışmada suya ait fizikokimyasal parametreler içeren bir tablosal su kalitesi veri seti kullanılmış ve veriler QR, Aztec ve Data Matrix kod görsellerine dönüştürülmüştür. Elde edilen barkod veri setleri, öncelikle aktarım öğrenme yaklaşımı kullanılarak MobileNet, MobileNetV2 ve MobileNetV3Small Evrişimsel Sinir Ağı (CNN) mimarileri ile 5-kat çapraz doğrulama yöntemi kapsamında değerlendirilmiştir. Ardından, en yüksek sınıflandırma performansı elde eden MobileNetV3Small modeli, CNN-Transformer mimarisinin omurgası olarak kullanılmış ve önerilen bu modelle görüntüler sınıflandırılmıştır. Deneysel sonuçlara göre, ortalama olarak en yüksek performans sonuçları Aztec kod veri setinde elde edilmiştir. Bu veri setinde MobileNetV3Small modeli $91,95 \pm 1,19$ ve MobileNetV3Small-Transformer modeli $97,72 \pm 2,19$ doğruluk değerleri elde etmiştir. Öte yandan, önerilen MobileNetV3Small-Transformer modeli QR kod veri setinde $92,65 \pm 5,88$ ve Data Matrix kod veri setinde $90,44 \pm 7,76$ doğruluk değerlerine ulaşmıştır. Önerilen yaklaşım, çevresel veri analitiği alanında tablosal verilerin görsel temsiller ve DL yöntemiyle değerlendirilmesine yönelik alternatif bir çözüm sunmaktadır.

Anahtar Kelimeler: Su kalitesi, tablosal veriler, barkod görüntüleri, evrişimsel sinir ağları, transformer mimarisi

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1 Asst. Prof. Dr., Isparta University of Applied Sciences, Uluborlu Selahattin Karasoy Vocational School, Department of Computer Technologies, Isparta, Türkiye, birkanbuyukarikan@isparta.edu.tr

2 Asst. Prof. Dr., Selçuk University, Silifke Taşucu Vocational School, Department of Construction, Mersin, Türkiye, zyilmaz@selcuk.edu.tr

*Corresponding Author: Birkan Büyükarıkan
birkanbuyukarikan@isparta.edu.tr

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1. Introduction

Water is a vital natural resource that is essential for sustaining life. Maintaining water quality is crucial for protecting human health, preserving the environment, and supporting economic growth. However, with the rise of industrialization, urbanization, and agricultural activities, water pollution has become a significant global concern. Water quality refers to the overall condition of water, characterized by its chemical, physical, and biological properties. Various anthropogenic activities frequently release harmful substances, including excess nutrients, pollutants, and heavy metals, which can significantly degrade water quality (Essamlali et al., 2024; Makumbura et al., 2024).

Although traditional water quality analysis methods are generally regarded as reliable, they exhibit several notable limitations. These methods are often costly, time-consuming, and dependent on specialized laboratory infrastructure (Ahmed et al., 2019b). Water samples must be collected in the field and transported to laboratories, which may delay the availability of results. Moreover, the analytical procedures themselves are typically complex and labor-intensive, limiting their suitability for rapid or large-scale water quality assessment (Ahmed et al., 2019a). To address these challenges, automated remote monitoring devices have been developed. These systems enable continuous data collection, and the resulting data can be transmitted over communication networks for analysis and processing. However, concerns remain regarding privacy, reliability, and security when using these systems for long-term water quality monitoring. Additionally, the cost of implementing these systems can be prohibitive (Azroul et al., 2022). Accurate and effective assessment of water quality is therefore essential for predicting future conditions (Ahmed et al., 2019b). Traditional process-based modeling methods rely on datasets that require significant processing time and often contain many input variables (Ahmed et al., 2019a). At this point, machine learning (ML) methods, which enable the automation of water quality estimation and analysis, have emerged as a powerful alternative. ML offers faster, more accurate, economical, and scalable solutions compared to traditional modeling approaches and has become an indispensable tool, particularly for real-time monitoring and complex data analysis requirements (Ahmed et al., 2019b). The literature reports successful applications of various ML models, such as multi-layer perceptron (MLP), eXtreme Gradient Boosting, artificial neural networks, decision trees, support vector machines (SVM), k-nearest neighbors (KNN), and random forests for water quality assessment (Ahmed et al., 2019a; Turan, 2023; Kirui, 2024; Elmotawakkil et al., 2025).

In recent years, deep learning (DL) architectures have become widely adopted for classifying water quality. Thanks to its ability to learn from high-dimensional, complex data, the DL method offers significant advantages, particularly for assessing water quality over time (Dilmi and Ladjal, 2021). Among these architectures, deep neural networks (DNNs), long short-term memory (LSTM), and gated recurrent units (GRU) are preferred due to their ability to model complex and temporal patterns in water quality data (Haq and Harigovindan, 2022; Prasad et al., 2022; Chellaiah et al., 2024). For example, Arabelli et al. (2025) proposed a DNN model to determine water quality in aquaculture using tabular data, achieving an accuracy of 95.69%. Similarly, Karpagam and Christy (2024) proposed a Stacked Ensemble Efficient LSTM model to classify water quality indices, achieving an accuracy of 98.85%.

Among other DL architectures, convolutional neural networks (CNNs) and vision transformers (ViTs) have brought significant advances in image recognition and classification tasks (He et al., 2016). CNNs have an inherent local bias because they focus on local feature extraction (König et al., 2025), whereas ViTs offer state-of-the-art performance in many visual tasks thanks to their ability to model global context (Roy et al., 2024). Recent studies using CNNs have assessed water quality by analyzing spectrograms and remote sensing data. The CNN's layers enable it to automatically learn complex patterns such as water color, turbidity, and the presence of algae (Ali et al., 2025; Bhatlawande et al., 2025; de Fleury et al., 2025; Fernández-Manteca et al., 2025). In these water quality studies, researchers have generally used well-known CNN architectures. Bhatlawande et al. (2025) classified water images as clean or polluted with 83.99% accuracy using the CNN model. Similarly, Gour et al. (2024) evaluated images obtained from water sources using a CNN to classify various types of pollution. In that study, which used 228 images, the authors achieved 97% accuracy with their proposed model. Furthermore, Nie et al. (2025) used a CNN to classify water turbidity, achieving 96.5% accuracy with their proposed CNN-10 model.

The success of CNNs in image-based classification has prompted researchers to explore the use of two-dimensional visual representations for non-image data, such as time series and tabular data (Zhu et al., 2021; Erol Doğan and Uzbaş, 2023; Gómez-Martínez et al., 2024; Gür et al., 2025). In this context, methods such as Gramian Angular Fields, Markov Transition Fields (Wang and Oates, 2015b; 2015a), ASCII code (Gür et al., 2025), and barcode-based encoding (Toğaçar, 2026) have been proposed to convert tabular data into visual representations. Two-dimensional barcode systems, such as QR, Aztec, and Data Matrix codes, have been identified as particularly promising due to their high data density, error correction capabilities, and standardized

structures (Querini and Italiano, 2012; Khadilkar and Stamp, 2025; Ladino and Sama, 2025; Noever and McKee, 2025). In the current literature, water quality assessment is primarily based on methods that rely on tabular data or on direct image-based approaches. In contrast, a hybrid approach that utilizes visual representations of parametric measurements can combine the accuracy of physicochemical data with the advantages of visual pattern recognition. Accordingly, to combine the strengths of CNN and Transformer architectures, this study adopts a hybrid CNN-Transformer approach that simultaneously learns local and global features for analyzing barcode representations.

The aim of this study is to classify tabular water quality data by transforming them into two-dimensional barcode-based visual representations. In this context, three different datasets based on QR, Aztec, and Data Matrix codes were created using the publicly available tabular Aquaculture Water Quality Dataset (WQD). The MobileNet, MobileNetV2, and MobileNetV3Small models were evaluated on these datasets using a 5-fold cross-validation procedure with a transfer learning approach. The CNN model with the highest mean performance was then combined with Transformer components to form a hybrid CNN-Transformer model for water quality image classification. Additionally, an ablation study was conducted to assess the impact of the number of attention heads in the Transformer architecture. Furthermore, the WQD tabular data were also evaluated using traditional ML models. The main contributions of this study to the literature are summarized as follows:

(i) Tabular data were transformed into barcode-based visual representations using three different two-dimensional coding methods and subsequently analyzed using CNN architectures. This enabled analysis of the effects of different visual coding strategies on the classification performance of DL architectures and facilitated the identification of the most suitable visual representation.

(ii) The model that achieved the highest performance in this study was used as the backbone in the proposed CNN-Transformer model. This approach enhanced the representational power of the proposed model and contributed to improved generalization performance. Additionally, the impact of the CNN-Transformer model's head component was analyzed through an ablation study.

2. Materials and Methods

2.1. Dataset overview and tabular-to-visual data conversion

In this study, the WQD developed by Veeramsetty et al. (2024) the researchers was used to assess water quality in aquaculture. The WQD was obtained from the Mendeley platform as a publicly available tabular dataset containing water quality indicators. It includes various physical and chemical parameters such as temperature, turbidity, dissolved oxygen, biochemical oxygen demand (BOD), carbon dioxide (CO₂), pH, alkalinity, hardness, calcium, ammonia, nitrite, phosphorus, hydrogen sulphide (H₂S), and plankton. Water quality in the dataset is categorized into three classes: excellent (class 0), good (class 1), and poor (class 2). The dataset comprised 4300 samples, including 1400 excellent quality, 1400 good quality, and 1500 poor quality samples (Veeramsetty et al., 2024; Arabelli et al., 2025). Figure 1 shows the distributions of each feature in the dataset. Since there were no missing values, no data preprocessing was applied. However, the features were not normalized before being converted into barcode images, and all analyses were performed directly on the raw data values.

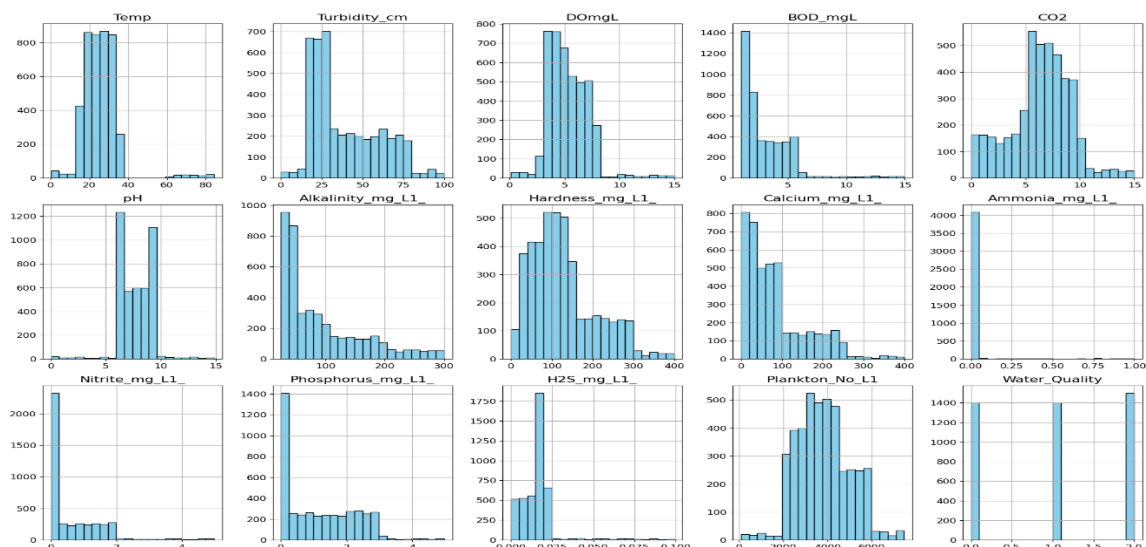


Figure 1. Distribution of features in the WQD dataset

In this study, tabular data from the WQD were transformed into two-dimensional barcode-based visual representations for evaluation using CNN-based models. Specifically, the feature vector of each sample was encoded as an image using QR code, Aztec code, and Data Matrix (ECC200 - Error Correction Code 200) formats. This transformation enables a more effective capture of the spatial and structural patterns inherent in the data.

The Python programming language was used to generate the barcodes. The qrcode library was employed for QR code generation, the zint library for Aztec codes, and the pylibdmtx library for Data Matrix codes. The original column order defined in the tabular dataset was preserved during encoding. All images were scaled to 224×224 pixels, and a total of 4300 grayscale images were stored in PNG format. These grayscale images were then expanded to RGB format to meet the three-channel input requirement of CNN-based models. Thus, each sample was converted into a three-channel image suitable for CNN processing. Geometric data augmentation of barcode representations was not applied, as it may disrupt the code structure. Figure 2 shows example images from the datasets created in this study.

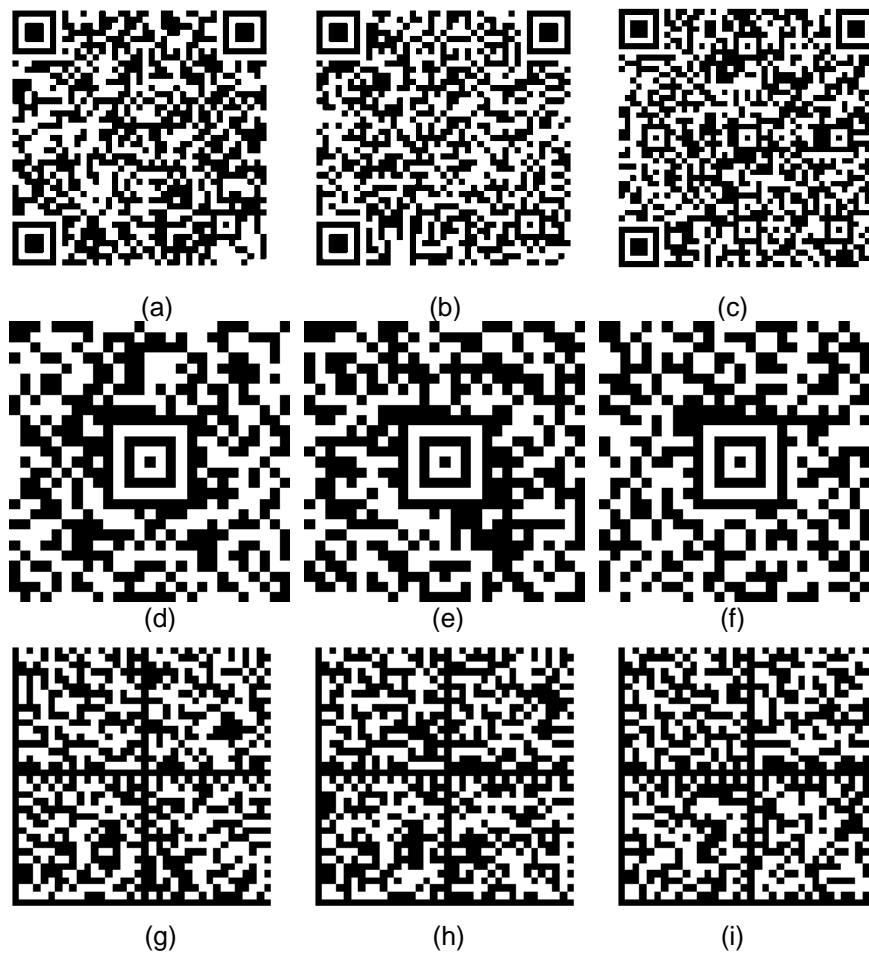


Figure 2. Sample images from the WQD tabular dataset converted to images, (a) QR code excellent quality class, (b) QR code good quality class, (c) QR code poor quality class, (d) Aztec code excellent quality class, (e) Aztec code good quality class, (f) Aztec code poor quality class, (g) Data Matrix code excellent quality class, (h) Data Matrix code good quality class, (i) Data Matrix code poor quality class

2.2. Deep learning-based classification models

2.2.1. MobileNet versions convolutional neural network architectures

MobileNet, MobileNetV2, and MobileNetV3Small are CNN models designed for deployment on systems with limited hardware resources (Taha et al., 2022). These models are computationally efficient, with MobileNet reducing both parameter count and computational cost through depthwise separable convolutions (Howard et al., 2017). MobileNetV2 further improves upon this design by incorporating inverted residual blocks and linear bottleneck layers to enhance accuracy and representational capacity (Sandler et al., 2018). MobileNetV3Small extends these optimizations by leveraging Neural Architecture Search and model compression techniques,

achieving competitive performance with reduced latency and energy consumption. This improvement is facilitated by the h-swish activation function and squeeze-and-excitation blocks (Howard et al., 2019). In this study, the MobileNet, MobileNetV2, and MobileNetV3Small architectures are employed as feature extractors to support both classification and efficient representation learning of barcode-based visual data.

2.2.2. CNN-Transformer classification model

Transformer-based architectures have demonstrated high performance in modeling the global context in natural images (Dosovitskiy, 2020). However, the barcode representations used in this study consist of structured patterns rather than natural image content. As a result, purely Transformer-based approaches may not capture sufficiently relevant features from these representations (Duan et al., 2025). Therefore, to address this limitation, this study proposes a hybrid CNN-Transformer classification approach that combines local feature extraction via CNNs with global dependency modeling via Transformers (Tanwar et al., 2025).

In this study, $224 \times 224 \times 3$ -dimensional images were first converted into high-level feature maps using the MobileNetV3Small backbone, pre-trained on ImageNet. The resulting features were projected into a fixed 128-dimensional embedding space via a 1×1 convolutional layer and then converted into tokens while preserving the two-dimensional spatial structure. The resulting token sequences were processed in two parallel streams within the Dual-Stream block designed for this study. In the local stream (ConvStream) learns local spatial information from neighborhood relationships using successive 3×3 convolution-based layers in a 64-channel subspace. In the global stream (TransformerStream), global dependencies were modeled using a multi-head self-attention mechanism with 8 attention heads, where each head simultaneously captures different feature relationships in the data. The outputs from both streams were then fused via a linear layer, integrating local and global representations into a shared feature space. In the final stage (Figure 3c), a single feature vector was obtained via Global Average Pooling 1D, followed by a Batch Normalization layer to normalize the activations. Subsequently, a hidden layer with 64 neurons was applied, incorporating an L2 regularization term and the ReLU activation function. Additionally, a second Batch Normalization layer was included to further improve the model stability, and a dropout layer with a rate of 0.5 was employed to prevent overfitting. The proposed approach is presented in detail in Figure 3. Figure 3a illustrates the dataset creation process. Figure 3b shows the use of the MobileNet, MobileNetV2, and MobileNetV3Small architectures in transfer learning. Figure 3c depicts the overall architecture of the proposed model.

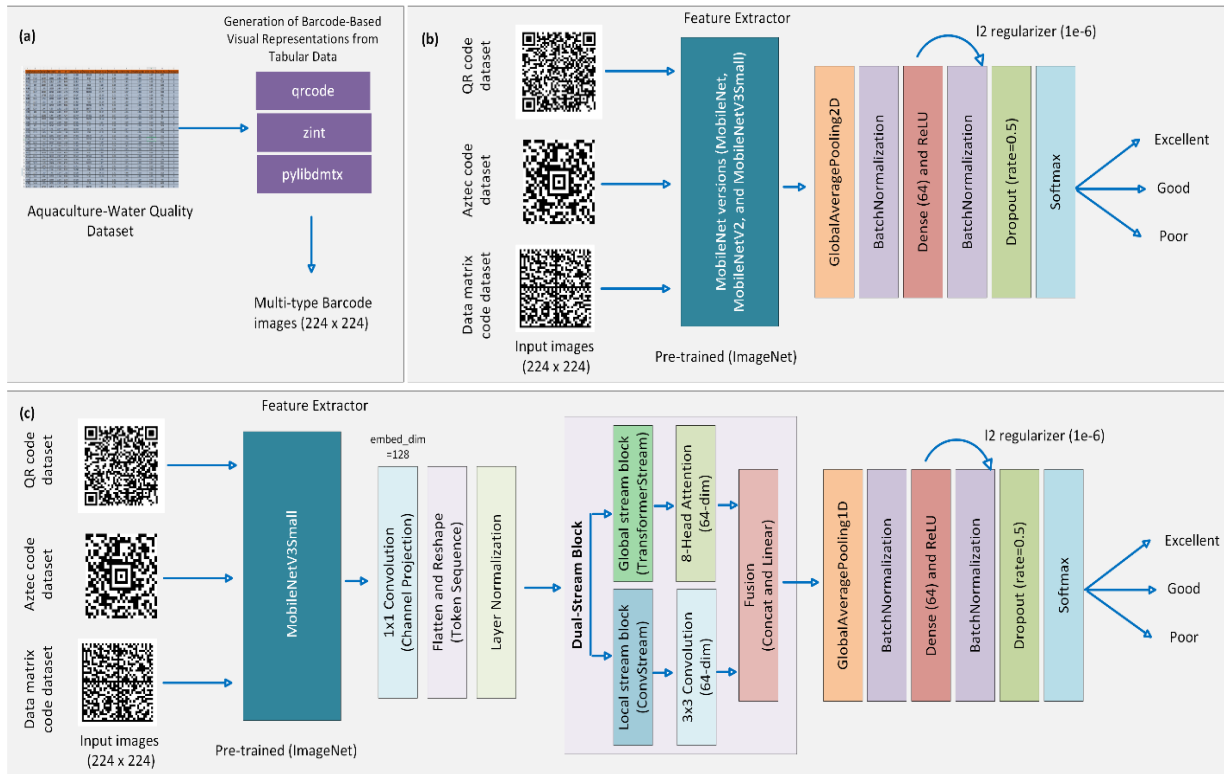


Figure 3. Basic diagram of the proposed model, (a) Generating barcode images, (b) MobileNet versions CNN models, (c) CNN-Transformer classification model

2.3. Proposed approach and experimental setup

This study proposes an approach for classifying water quality by transforming tabular data into two-dimensional visual representations and using DL architectures for classification. The tabular water quality data were converted into visual datasets using three different two-dimensional barcode formats: QR, Aztec, and Data Matrix codes. A 5-fold cross-validation method was used to evaluate the performance of the proposed models, and the results are reported as the mean and standard deviation (SD) values. Each barcode dataset was classified using the MobileNet, MobileNetV2, and MobileNetV3Small architectures. These models were optimized via transfer learning with pre-trained ImageNet weights, and the best-performing model was selected as the backbone of the proposed architecture.

During the training process of the CNN and CNN-Transformer models, Sparse Categorical Crossentropy was used as the loss function. The Lion optimizer algorithm was selected for the optimization process, and a learning rate of 1e-4 was chosen (Kumar et al., 2025). During training, a batch size of 64 samples was used per epoch, and the models were trained for 20 epochs. However, a total of 54 iterations were performed in each epoch. A fixed “random state” value was used to ensure experimental reproducibility. Table 1 lists the parameter values used for training the models. All experiments were conducted in Python on the Google Colab using TPU v6e-1 hardware. An ablation study was also conducted to investigate the effect of the number of attention heads in the Multi-Head Self-Attention mechanism of the proposed CNN-Transformer model. In addition, the tabular data in the WQD dataset were classified using traditional ML models, including SVM, Logistic Regression (LR), MLP, Naive Bayes (NB), and KNN. For all ML models, default hyperparameter settings were used during training.

Table 1. Training parameters and values used in this study

Parameter	Value(s)
Loss function	Sparse Categorical Crossentropy
Optimizer	Lion
Clipnorm	1
Activation function	ReLU
Learning rate	1e-4
Batch size	64
Epoch	20
Number of iterations	54
Shuffle	True
Random state	42

2.4. Evaluation of the models

The metrics used to evaluate all models included accuracy, precision, recall, F1-score, Cohen’s Kappa, and area under the curve (AUC). The AUC values were computed using the roc_auc_score function from the scikit-learn library. The remaining evaluation metrics were calculated using Equations (1)–(5).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (3)$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision+Recall} \times 100 \quad (4)$$

$$Cohen's\ Kappa = \frac{P_{Acc} - P_e}{1 - P_e} \quad (5)$$

Here, TP represents True Positive, TN True Negative, FP False Positive, FN False Negative, P_{Acc} represents general classification accuracy, and P_e represents random accuracy rate. Accuracy, Precision, Recall, and F1-score values are reported as percentages (%), while AUC values are presented on a 0–1 scale and Cohen’s Kappa ranges between –1 and 1.

In addition, pooled confusion matrices were used to evaluate the models. Specifically, the individual confusion matrices obtained from 5-fold cross-validation were aggregated to produce a single cumulative matrix representing the entire dataset (Ravindran et al., 2023).

3. Results and Discussion

3.1. Evaluation of the proposed approach

The classification performance results of the MobileNet-based CNN models across various representations of two-dimensional barcodes are presented in Table 2. The experimental findings indicate that the MobileNetV3Small model generally attains superior classification performance across all datasets.

On the QR code, Aztec code, and Data Matrix code datasets, the MobileNetV3Small model achieved accuracy rates of 81.49±1.40%, 91.95±1.19%, and 81.79±1.05%, respectively. Specifically, on the QR code dataset, the MobileNetV3Small model demonstrated a precision of 81.44±1.47%, a recall of 81.73±1.39%, an F1-score of 81.37±1.43%, a Cohen’s Kappa value of 0.72±0.02, and an AUC value of 0.94±0.01. Similarly, on the Aztec code dataset, the MobileNetV3Small model’s precision, recall, F1-score, Cohen’s Kappa, and AUC metrics were 92.03±1.19%, 92.04±1.18%, 92.01±1.19%, 0.88±0.02, and 0.98±0.00, respectively. On the Data Matrix code dataset, the performance metrics were comparatively lower across all models; however, the MobileNetV3Small model, which achieved the highest performance within this dataset, recorded precision, recall, F1-score, Cohen’s Kappa, and AUC values of 81.86±1.14%, 82.08±1.04%, 81.85±1.09%, 0.73±0.02, and 0.94±0.00, respectively. This reduced performance may be attributed to the denser and more complex structure of Data Matrix codes, which pose greater challenges for CNN models in discerning visual distinctions. The results demonstrate that the MobileNetV3Small model outperformed other MobileNet variants in the classification tasks related to water quality on the QR code, Aztec code, and Data Matrix code datasets. Consequently, the MobileNetV3Small model was selected as the backbone for the CNN-Transformer model introduced subsequently in this study.

Table 2. Mean performance results of MobileNet version CNN models on various barcode datasets

Model	Accuracy (Mean±SD%)	Precision (Mean±SD%)	Recall (Mean±SD%)	F1-score (Mean±SD%)	Cohen’s Kappa (Mean±SD)	AUC score (Mean±SD)
QR code						
MobileNet	80.35±0.98	80.27±1.05	80.53±0.97	80.35±1.04	0.71±0.02	0.93±0.01
MobileNetV2	75.77±1.05	75.87±1.28	75.96±0.97	75.83±1.18	0.64±0.02	0.91±0.01
MobileNetV3Small	81.49±1.40	81.44±1.47	81.73±1.39	81.37±1.43	0.72±0.02	0.94±0.01
Aztec code						
MobileNet	88.84±0.89	88.89±0.92	88.96±0.86	88.90±0.91	0.83±0.01	0.98±0.01
MobileNetV2	88.74±1.40	88.90±1.31	88.85±1.43	88.84±1.37	0.83±0.02	0.98±0.00
MobileNetV3Small	91.95±1.19	92.03±1.19	92.04±1.18	92.01±1.19	0.88±0.02	0.98±0.00
Data Matrix code						
MobileNet	74.58±1.09	74.49±1.32	74.89±1.04	74.62±1.23	0.62±0.02	0.89±0.01
MobileNetV2	74.81±1.28	74.65±1.28	75.14±1.31	74.81±1.23	0.70±0.01	0.90±0.02
MobileNetV3Small	81.79±1.05	81.86±1.14	82.08±1.04	81.85±1.09	0.73±0.02	0.94±0.00

The best results are highlighted in bold.

Figure 4 illustrates the normalized pooled confusion matrices obtained from the MobileNetV3Small model across various barcode-based datasets. On the QR code dataset (Figure 4a), the model exhibits robust classification performance across all classes. As depicted in Fig. 4a, errors predominantly occur in Classes 1 and 2. Concerning the Aztec code dataset (Figure 4b), the model generally demonstrates balanced performance; however, it is observed that misclassifications are more concentrated in Class 2. Nevertheless, it can be asserted that the Aztec code representations bolster the distinction between classes and facilitate the model in producing more consistent results. Conversely, a notable decline in model performance is observed within the Data Matrix code dataset (Figure 4c). The clustering of misclassifications between Classes 1 and 2 suggests that the discriminative features derived from Data Matrix code representations are comparatively less distinctive than those of other barcode types.

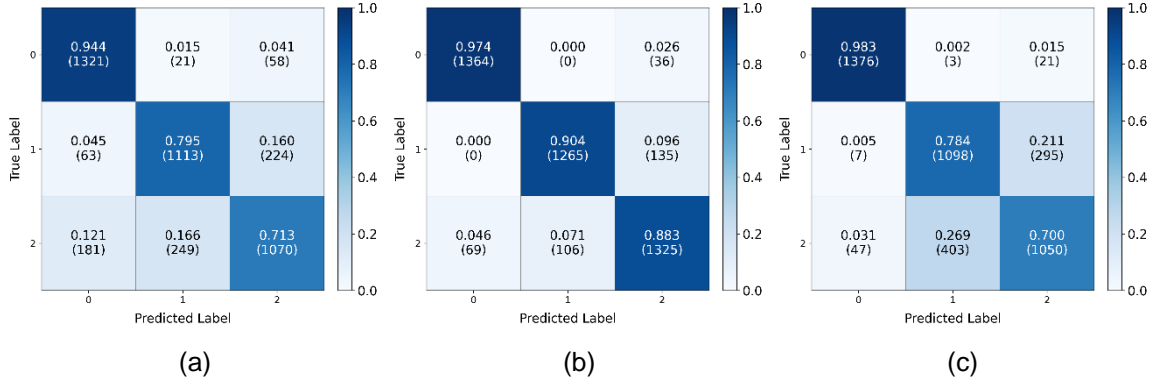


Figure 4. Normalized pooled confusion matrices obtained from barcode datasets for the MobileNetV3Small model (Class 0 is excellent quality, Class 1 is good quality, and Class 2 is poor quality): (a) QR code, (b) Aztec code, (c) Data Matrix code

The performance results of the MobileNetV3Small-Transformer model on various barcode-based datasets are presented in Table 3. On the Aztec Code dataset, the proposed model achieved $97.72 \pm 2.19\%$ accuracy, $97.88 \pm 1.96\%$ precision, $97.80 \pm 2.10\%$ recall, $97.74 \pm 2.18\%$ F1-score, 0.97 ± 0.03 Cohen’s Kappa, and 1.00 ± 0.00 AUC score. Although the highest performance was achieved on the Aztec code dataset, the proposed model still maintained high classification accuracy on the QR code and Data Matrix code datasets. These results suggest that the proposed model is less effective compared with Aztec code at capturing discriminative features from QR code and Data Matrix code representations.

Table 3. Mean performance results of the MobileNetV3Small-Transformer model

Dataset	Accuracy (Mean±SD%)	Precision (Mean±SD%)	Recall (Mean±SD%)	F1-score (Mean±SD%)	Cohen’s Kappa (Mean±SD)	AUC score (Mean±SD)
QR code	92.65±5.88	93.09±5.65	92.76±5.89	92.71±5.76	0.89±0.02	0.99±0.01
Aztec code	97.72±2.19	97.88±1.96	97.80±2.10	97.74±2.18	0.97±0.03	1.00±0.00
Data Matrix code	90.44±7.76	92.61±4.70	90.49±7.92	89.86±8.81	0.86±0.12	0.99±0.01

The best results are highlighted in bold.

Figure 5 presents the normalized pooled confusion matrices obtained for the proposed MobileNetV3Small-Transformer model across QR code (Figure 5a), Aztec code (Figure 5b), and Data Matrix code (Figure 5c) datasets. On the QR code dataset (Figure 5a), the model achieves a high classification accuracy for Classes 0 and 1. For the Aztec code dataset (Figure 5b), the model demonstrates high accuracy across all classes, indicating an effective capture of underlying feature representations and enhanced class separability. Conversely, a discernible decline in performance is observed in the Data Matrix code dataset (Figure 5c). Overall, the misclassifications are predominantly concentrated between Classes 1 and 2 across all datasets, potentially attributable to the similarity in their feature distributions.

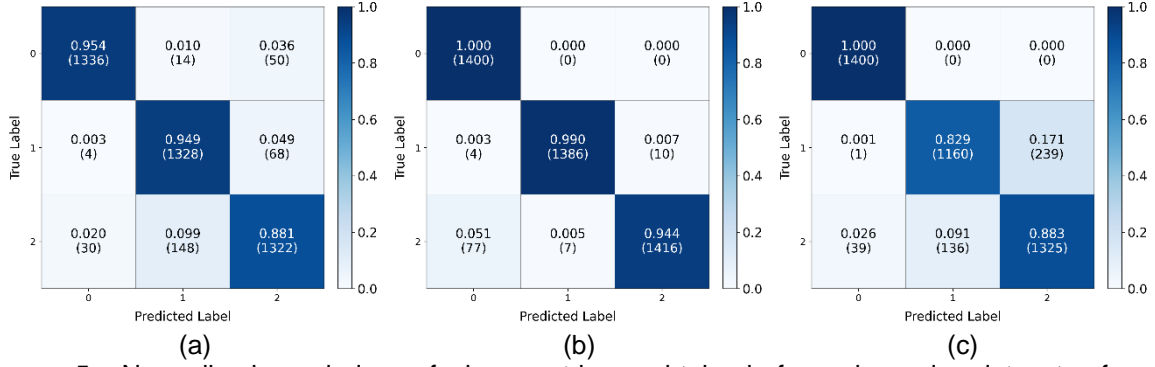


Figure 5. Normalized pooled confusion matrices obtained from barcode datasets for the MobileNetV3Small-Transformer model (Class 0 is excellent quality, Class 1 is good quality, and Class 2 is poor quality): (a) QR code, (b) Aztec code, (c) Data Matrix code

Figure 6 compares the average accuracies between the MobileNetV3Small and the proposed MobileNetV3Small-Transformer models across various barcode-based datasets. The MobileNetV3Small-Transformer model consistently achieved higher accuracy relative to the MobileNetV3Small model across all datasets. Specifically, on the QR code dataset, the accuracy increased from 81.49% to 92.65% (an improvement of 11.16%), while on the Aztec code dataset, the accuracy rose from 91.95% to 97.72% (a 5.77% improvement). Additionally, on the Data Matrix code dataset, the accuracy improved from 81.79% to 90.44% (an 8.65% increase). The results demonstrate that Transformer-based global context modeling provides a complementary function to CNN-based local feature extraction. It is also noteworthy that the relatively lower performance in QR and Data Matrix code representations may be attributed to their comparatively limited structural distinctiveness relative to Aztec codes.

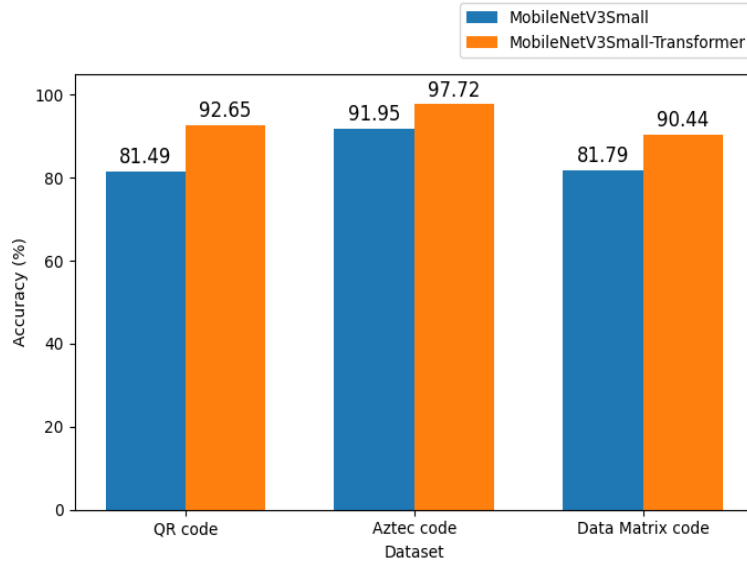


Figure 6. Comparison of the mean accuracy results of the proposed models

3.2. Ablation study

Table 4 reports the performance of the proposed CNN-Transformer model based on the number of attention heads in the Transformer component. It is observed that the quantity of heads used in the multi-head self-attention mechanism significantly influences the model's performance. When the number of heads was set to 8, the model attained high performance across QR code and Aztec code datasets. However, when the number of heads was set to 2, the model exhibited balanced performance across all datasets. In terms of accuracy, the model achieved $89.95 \pm 1.52\%$ on the QR code dataset, $95.47 \pm 3.25\%$ on the Aztec code dataset, and $92.65 \pm 7.36\%$ on the Data Matrix code dataset. An increase in the number of heads from 1 to 2 generally enhanced the performance. On the other hand, the performance variations observed in certain datasets with the number of heads set to 4 underscore the model's capacity to capture features.

Table 4. Mean performance results of the CNN-Transformer model by number of heads

Number of heads	Accuracy (Mean±SD%)	Precision (Mean±SD%)	Recall (Mean±SD%)	F1-score (Mean±SD%)	Cohen's Kappa (Mean±SD)	AUC score (Mean±SD)
QR code						
1	84.19±14.08	89.91±6.11	84.09±14.38	82.14±17.77	0.76±0.21	0.98±0.04
2	89.95±1.52	91.14±1.99	89.96±1.49	89.91±1.54	0.85±0.02	0.99±0.01
4	89.77±8.22	91.98±5.54	89.83±8.26	89.49±8.60	0.85±0.12	0.99±0.02
8	92.65±5.88	93.09±5.65	92.76±5.89	92.71±5.76	0.89±0.02	0.99±0.01
Aztec code						
1	95.30±5.03	96.28±3.52	95.30±5.13	95.32±5.04	0.93±0.08	1.00±0.00
2	95.47±3.25	96.10±2.63	95.56±3.13	95.50±3.23	0.93±0.05	1.00±0.00
4	91.28±7.04	93.52±4.40	91.45±6.82	91.29±7.08	0.87±0.11	0.99±0.01
8	97.72±2.19	97.88±1.96	97.80±2.10	97.74±2.18	0.97±0.03	1.00±0.00
Data Matrix code						
1	88.79±6.48	91.61±3.90	89.10±6.11	88.50±6.92	0.83±0.10	0.98±0.02
2	92.65±7.36	94.55±4.56	92.81±7.06	92.46±7.79	0.89±0.11	1.00±0.00
4	88.35±9.25	90.57±7.75	88.53±9.10	88.16±9.46	0.83±0.14	0.98±0.03
8	90.44±7.76	92.61±4.70	90.49±7.92	89.86±8.81	0.86±0.12	0.99±0.01

The best results are highlighted in bold.

3.3. Analysis of tabular data using traditional machine learning models

Table 5 lists the average classification performance of traditional ML models, including SVM, LR, MLP, NB, and KNN, on tabular water quality data. The experimental results indicate that the SVM model achieved the highest mean classification performance. Specifically, the accuracy, precision, recall, F1-score, Cohen's Kappa, and AUC values for this model were 90.19±2.81%, 91.64±2.42%, 90.61±2.69%, 89.94±3.15%, 0.85±0.04, and 0.97±0.02, respectively. On the other hand, LR showed limited capacity in capturing inter-class separability and achieved a lower AUC than the other models. Although ML models yielded competitive results, the proposed CNN-Transformer model achieved superior performance owing to its capability to learn more complex patterns from barcode representations.

Table 5. Mean performance results of traditional ML models

Model	Accuracy (Mean±SD%)	Precision (Mean±SD%)	Recall (Mean±SD%)	F1-score (Mean±SD%)	Cohen's Kappa (Mean±SD)	AUC score (Mean±SD)
SVM	90.19±2.81	91.64±2.42	90.61±2.69	89.94±3.15	0.85±0.04	0.97±0.02
LR	78.09±4.36	78.75±4.18	78.78±4.13	76.62±5.78	0.67±0.06	0.85±0.06
MLP	85.56±4.16	87.62±3.17	86.13±3.97	84.87±4.83	0.78±0.06	0.91±0.05
NB	88.56±3.84	90.67±3.07	89.07±3.67	88.10±4.36	0.83±0.06	0.96±0.05
KNN	76.28±1.17	82.72±1.05	77.33±1.12	72.76±1.85	0.65±0.02	0.88±0.04

The best results are highlighted in bold.

3.4. Discussion

Table 6 summarizes previous studies on water quality classification in terms of data type, number of data, the model used, and the accuracy metric. Since no prior study directly aligns with the approach proposed in this study, the comparison focuses on the reported accuracy of DL-based methods. Karpagam and Christy (2024) achieved 98.85% accuracy in classifying water quality indices using a Stacked Ensemble Efficient LSTM model. Arabelli et al. (2025) used a DNN model for water quality classification, achieving 95.69% accuracy with their proposed model. On the other hand, Bhatlawande et al. (2025) classified clean and polluted water images with 83.99% accuracy using their proposed CNN model. Similarly, Gour et al. (2024) classified various water pollution images with 97% accuracy using their CNN model. Furthermore, Nie et al. (2025) achieved an accuracy of 96.5% using the CNN-10 model to classify water turbidity.

In this study, tabular data were converted into a barcode-based visual representation. The MobileNetV3Small model achieved an average accuracy of 91.95% on the Aztec code dataset, while the MobileNetV3Small-Transformer model achieved 97.72%. Previous studies in the literature have relied primarily on tabular data or water images. In contrast, the proposed approach leverages visual representations of the data to exploit the advanced pattern recognition capabilities of the CNN-Transformer model.

The findings indicate that barcode-based representations provide a more distinctive input for CNN models while preserving the structural characteristics of tabular data. The higher performance observed for Aztec codes is attributed to the Transformer's global attention mechanism, which more effectively captures the distinctive features of Aztec code's data layout. On the other hand, QR and Data Matrix codes exhibit lower performance, likely because their encoding structures are less visually distinctive and therefore less informative for feature extraction.

Table 6. Comparison with previous works

Reference	Data type	Count of data / image	Model	Accuracy (%)
Karpagam and Christy (2024)	Tabular data	3276	Stacked Ensemble Efficient LSTM	98.85
Arabelli et al. (2025)	Tabular data	4300	DNN	95.69
Bhatlawande et al. (2025)	Image	200	CNN	83.99
Gour et al. (2024)	Image	228	CNN	97
Nie et al. (2025)	Image	250	CNN-10	96.5
This study	Image (Aztec code)	4300	MobileNetV3Small	91.95
This study	Image (Aztec code)	4300	MobileNetV3Small-Transformer	97.72

3.5. Environmental applications and implications

One of the most significant environmental benefits of the proposed approach is its potential integration into real-time water quality monitoring systems. The time-consuming and costly nature of traditional analytical methods limits large-scale monitoring efforts. In contrast, the literature demonstrates that the Internet of Things and ML can provide continuous data streams that enable real-time analysis and early warning mechanisms (Essamlali et al., 2024; Sawant and Patil, 2024). In this context, the proposed approach supports rapid, automatic classification by converting sensor data into barcode-based visual representations, thereby facilitating the early detection of sudden changes in water quality, particularly in aquaculture systems.

The barcode-based visual representations used in this study offer significant advantages not only for data transformation but also for data integrity and standardization. These representations allow heterogeneous data obtained from different sources to be consolidated within a unified structure, thereby facilitating data integration. The literature clearly emphasizes that DL-based approaches can effectively process such complex data structures to extract meaningful patterns (Toumi et al., 2024; Zhi et al., 2024). Accordingly, the superior performance observed, particularly with the Aztec code dataset, demonstrates that the proposed method can be reliably and effectively employed in environmental monitoring applications.

3.6. Limitations of this study

(i) The dataset used in this study consists solely of tabular data related to water quality. Therefore, the

generalizability of the proposed approach to other types of environmental data, such as air pollution or soil quality, has not been evaluated in this work. Additionally, real-time data were not utilized.

(ii) The DL architectures used in this study were trained using fixed hyperparameter configurations. Moreover, because geometric or pixel-based data augmentation applied to barcode-based visual representations can distort the barcode structure, no data augmentation strategies were implemented.

(iii) In this study, different MobileNet variants were evaluated, and only the Transformer component was integrated only into the architecture that yielded the highest performance.

4. Conclusion and Future Works

This study proposes a novel approach for classifying traditional tabular water quality data using DL models after converting the data into two-dimensional barcode-based visual representations. In this context, tabular water quality data were transformed into visual datasets utilizing QR, Aztec, and Data Matrix codes. These visual representations were subsequently assessed using MobileNet-based CNNs with 5-fold cross-validation.

The experimental results indicate that the MobileNetV3Small model demonstrated the highest performance across all barcode datasets. Specifically, these models achieved accuracy rates of $81.49 \pm 1.40\%$, $91.95 \pm 1.19\%$, and $81.79 \pm 1.05\%$ on the QR codes, Aztec codes, and Data Matrix code datasets, respectively. The MobileNetV3Small model served as the backbone for the development of the proposed CNN-Transformer model, achieving accuracies of $92.65 \pm 5.88\%$, $97.72 \pm 2.19\%$, and $90.44 \pm 7.76\%$ across the same datasets. The proposed MobileNetV3Small-Transformer model demonstrated improved classification performance across all datasets compared to alternative models.

The results substantiate that converting tabular data into barcode-based visual representations and analyzing these through hybrid DL architectures provides an effective strategy for water quality classification. Future research may involve evaluating the performance of the proposed approach using datasets sourced from diverse environmental sources.

5. Data availability

The data used in this study were obtained from an open-access dataset available on the Mendeley Data platform, as cited in Veeramsetty et al. (2024). The dataset is accessible at the following URL: <https://data.mendeley.com/datasets/y78ty2g293/1>

6. Compliance with Ethical Standard

a) Author Contributions

1. BB: Conceptualization, Methodology, Software, Data curation, Visualization, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing.

2. ZG: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing.

b) Conflict of Interests

There is no conflict of interest, according to the authors.

c) Statement on the Welfare of Animals

Not relevant.

d) Statement of Human Rights

There are no human subjects in this study.

e) Declaration of Not Using AI

The authors declare that they did not use any generative artificial intelligence in the writing of this article, or in the creation of the images, graphs, tables, or their corresponding headings.

f) Funding

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