Efficient Biomedical Waste Management: Optimizing Segmentation and Classification with EnU-Net-DNN-BMWC

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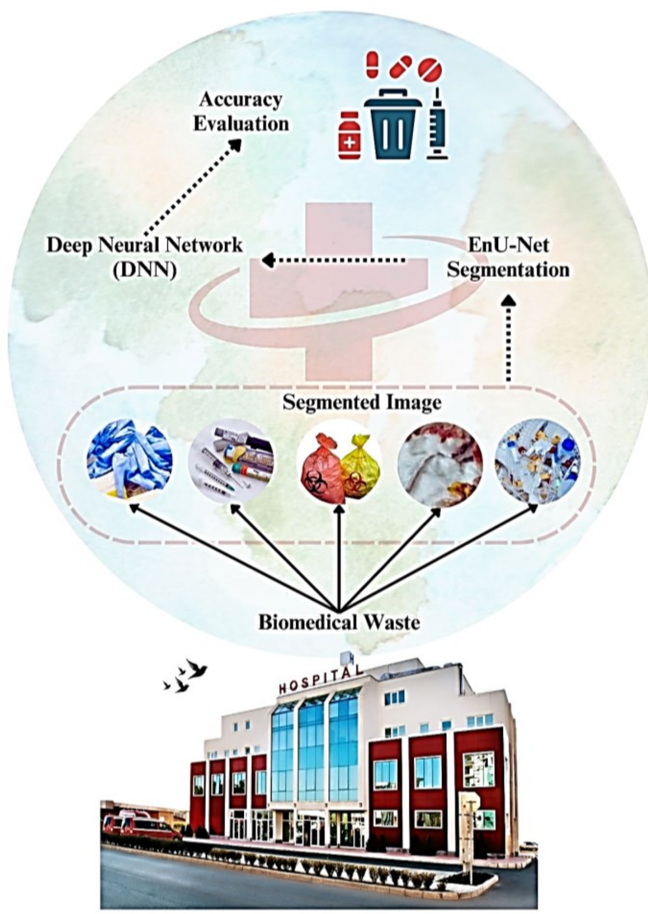
GRAPHICAL ABSTRACT



Abstract

In India, biomedical waste (BMW) management is governed by strict regulations to mitigate health and environmental risks. It includes materials such as sharps, infectious wastes, pharmaceuticals, and non-hazardous items contaminated with potentially infectious substances. Proper management and disposal of BMW are critical to prevent environmental contamination and health risks. This article introduces an Enhanced U-Network (EnU-Net) integrated with Deep Neural Network BMW Classification (EnU-Net-DNN-BMWC) to enhance accuracy in this critical task. Leveraging the U-Net framework with an Encoder-Decoder Network (EDN) and pixel-wise classification layer initially optimizes image segmentation. Bayesian functions mitigate segmentation uncertainties, while Content-Sensitive Sampling (CSS) refines pixel sampling to prioritize data-sparse regions. Data collected from G. Kuppuswamy Naidu Memorial Hospital and Kovai Medical Center and Hospital (KMCH) in Coimbatore over six months, categorizing sharps, infectious materials, pharmaceuticals, and non-hazardous waste, informs waste management strategies. Experimental validation using 100 biomedical waste images demonstrates EnU-Net-DNN-BMWC achieving good accuracy, surpassing standalone DNN-BMWC using Matlab 2022. The comparative analysis across different metrics such as accuracy, precision, F-measure, recall, error rate, and RMSE between DNN-BMWC and the proposed EnU-Net-DNN-BMWC framework were evaluated in this study, highlighting EnU-Net-DNN-BMWC's superior performance. Finally, this study underscores EnU-Net-DNN-BMWC's efficacy in enhancing biomedical waste classification, crucial for sustainable waste management practices and regulatory compliance in healthcare settings.

Keywords: *Biomedical waste, deep learning, U-Net, encoder, decoder, Deep Neural Network*

1. Introduction

The management and disposal of biomedical waste (BMW), a consequence of healthcare operations, presents substantial issues. It includes a wide range of substances, including medicines, contaminated materials, sharps, and medical trash. Minimizing health risks and environmental damage requires proper characterization and management of BMW. Precise division and categorization of these waste products are necessary for their proper removal and handling, ensuring that dangerous elements are managed appropriately and cutting down on total waste management expenses. The manual sorting and categorization method used in biomedical waste management is labor-intensive and frequently inconsistent. Automated systems that use machine learning and computer vision techniques have been presented as solutions to these problems. These technologies use sophisticated image processing and classification techniques to improve BMW management's accuracy and efficiency.

The Enhanced U-Network (EnU-Net) is specifically designed for precise image segmentation, making it ideal for identifying various biomedical waste types in complex images. Its encoder-decoder structure captures both global and local features, ensuring accurate delineation of waste items. The Deep Neural Network (DNN) complements this by effectively classifying the segmented outputs based on learned patterns. By integrating these two architectures within the EnU-Net-DNN-BMWC framework, we capitalize on U-Net's segmentation capabilities to provide detailed inputs for the DNN, thereby enhancing classification accuracy. This synergy results in a more robust and efficient system for biomedical waste management.

In this regard, an important advancement in this field is the suggested Enhanced Segmentation Network (EnU-Net), combined with a Deep Neural Network for Biomedical Waste Classification (EnU-Net-DNN-BMWC). Building on the U-Net architecture, a well-known model for medical picture segmentation, is the EnU-Net framework. Because U-Net is capable of fine-grained picture segmentation, its architecture combines an Encoder-Decoder Network (EDN) with a pixel-wise classification layer. To extract hierarchical characteristics from the image, the encoder gradually reduced. Then, the decoder upsamples these features to restore the spatial resolution, enabling accurate pixel-level classification. The U-Net framework does have certain drawbacks, despite its effectiveness. The inherent ambiguity in segmentation resulting from different image qualities and various waste compositions is one prominent obstacle. In order to tackle this issue, the EnU-Net architecture incorporates uncertainty estimates through the integration of Bayesian functions, hence enabling more resilient pixel sampling and minimizing segmentation mistakes.

The application of Bayesian functions to mitigate segmentation uncertainties is indeed a valuable strategy. To enhance the manuscript, it would be beneficial to provide a comprehensive overview of the implementation process of these functions. This includes detailing how prior distributions are defined, how likelihoods are calculated from segmentation outputs, and how posterior distributions are derived to update model predictions.

Additionally, discussing the specific types of Bayesian methods used, such as Bayesian inference or Monte Carlo sampling, would clarify their roles in reducing uncertainty. It's also important to present quantitative results demonstrating the impact of these Bayesian functions on model performance, such as improvements in accuracy, precision, and recall. Including visual examples of segmentation outputs before and after applying Bayesian methods could further illustrate their effectiveness, thus enriching the overall understanding of their contribution to the model's robustness.

Moreover, Content-Sensitive Sampling (CSS) is implemented by the framework to improve segmentation precision in data-sparse regions. In locations with less information, CSS deliberately gives detailed pixel sampling priority, while in denser areas, it conserves processing resources. By streamlining the segmentation procedure, this method guarantees a more accurate analysis of crucial areas. The potential of the EnU-Net-DNN-BMWC system to transform biomedical waste management procedures is highlighted by this study. It provides a promising way to raise the effectiveness and precision of BMW disposal and treatment procedures, which will ultimately lead to better environmental and public health results. It does this by fusing improved segmentation with sophisticated classification approaches.

Some recent kinds of literature provide valuable insights into different aspects of biomedical waste management, highlighting the role of technology and innovative approaches in addressing this critical issue. A range of artificial intelligence (AI) methods improve trash management procedures, including prediction models for waste generation and machine learning algorithms for waste classification. The focus of the article is on how AI can optimize resource allocation, enhance accuracy, lower human error, and update waste management procedures (Sarkar et al., 2023)

Using multivariate recurrent neural networks, a sophisticated method for anticipating the creation of biological waste during sanitary situations was provided by (Galvan-Alvarez et al. 2023). Their research highlights how improving waste management systems in urban environments requires precise forecasting models. This method ensures prompt intervention, reduces health hazards associated with inappropriate waste treatment, and improves readiness and resource allocation during emergencies. New technologies that support efficient BMW disposal and long-term management, especially in the context of the COVID-19 pandemic were investigated by (Kumbhar et al., 2024). They talk about a range of technologies that handle the spike in the creation of biological waste during the epidemic, including automated waste processing systems and sophisticated sterilization techniques. In order to increase effectiveness and safety, this analysis emphasizes how crucial it is to incorporate new technology into the frameworks already in place for waste management. Research on the use of artificial intelligence (AI) in the management of biomedical waste has been extensive. (Sengeni et al. 2023) offer AI-based approaches for managing biological waste with an emphasis on improving safety and streamlining disposal procedures. Their work offers insights into how artificial intelligence (AI) might improve and automate waste sorting and processing, hence streamlining waste management methods. It is included in the Handbook of Research on Safe Disposal Methods of Municipal Solid Wastes.

By presenting forth an IoT-tracked, fuzzy classified integrated technique for biomedical waste management, (Wawale et al. 2022) also contribute to this field. Their method tracks and classifies waste in real time using fuzzy logic and Internet of Things (IoT) technologies, guaranteeing more precise and effective management. The environmental effects of dental clinics' biomedical waste management are discussed by (Subramanian et al. 2021). Their research raises important questions about how biomedical waste is disposed of in dental settings, emphasizing the need for improved procedures and adherence to laws in order to prevent environmental harm. The understanding of BMW's environmental impact is deepened by this collaboration, especially in specialized sectors like dentistry.

However, the prospects, difficulties, and current developments in the field of biomedical waste management (Kannadhasan and Nagarajan 2022). Their analysis offers a thorough summary of contemporary problems and developments, including the application of deep learning and machine learning methods to improve waste management procedures. The focus of this work is on how BMW management is changing and how technology might help solve long-standing problems. (Achuthan and Madan Gopal 2016) explain the accuracy and efficiency of waste segregation are critical for efficient waste management, and this study offers a novel way to increase these metrics. To improve waste processing, the hybrid model combines the benefits of optimization and clustering methodologies.

Additionally, a fuzzy TOPSIS-based method for the thorough assessment of biological waste management. By adding fuzzy logic to the evaluation process, this approach promotes sustainability and decision-making by allowing for more accurate and nuanced analyses of waste management techniques (Al-Sulbi et al. 2023). Their efforts aid in the creation of stronger frameworks for assessing and enhancing BMW management systems. (Zulqarnain et al. 2024) use an interval-valued q-rung ortho-pair fuzzy soft set-based EDAS algorithm to evaluate different biomedical waste disposal methods. A thorough analysis of disposal strategies, stressing the advantages and disadvantages of various approaches in different situations. Their method offers insightful information on improving disposal procedures through quantitative evaluations (Gopi et al., 2020).

Biomedical waste management has been significantly impacted by the COVID-19 epidemic. The pandemic's effects on the buildup of biomedical waste are discussed by (Pavithiran et al. 2022), who also offer practical treatment solutions. Their research emphasizes how urgently strong waste management solutions are needed to address the pandemic's increased trash generation and related issues. The COVID-19 crisis's effects on waste management policy adherence and practices are reviewed by (Costa et al. 2023). Their narrative study clarifies how the pandemic has impacted waste management practices and regulations, offering a critical viewpoint on the necessity of more stringent management protocol adherence as well as adaptive methods.

2. Proposed Methodology

2.1. Data collection

Data for biomedical waste was collected from two prominent hospitals in Coimbatore, namely G. Kuppuswamy Naidu Memorial Hospital and Kovai Medical Center and Hospital (KMCH). The study focused on analyzing waste types, quantities, and composition to develop a comprehensive understanding of waste management practices in healthcare settings. Collected over six months, the data included detailed categorization of biomedical waste such as sharps, infectious materials, pharmaceuticals, and non-hazardous waste. This information is crucial for optimizing disposal strategies and ensuring compliance with regulatory standards. The empirical data gathered from these hospitals forms the basis for assessing current practices and proposing efficient, sustainable solutions in biomedical waste management tailored to local conditions in Coimbatore.

2.2. Dataset

This research uses MATLAB 2022 to compare the EnU-Net-DNN-BMWC framework's performance against that of the DNN-TC framework. 200 images of various biomedical wastes are used to evaluate the frameworks. These images are divided into five categories: sharp waste (scalpels, blades, and needles), pharmaceutical waste (residual medications and spills), infectious waste (discarded gloves, masks, and blood-soaked bandages), and pathological waste (solids and surgical fluids). For training and testing, the dataset is divided into 100 photos each. Figure 1 displays graphic depictions of example photos from the biomedical waste dataset.

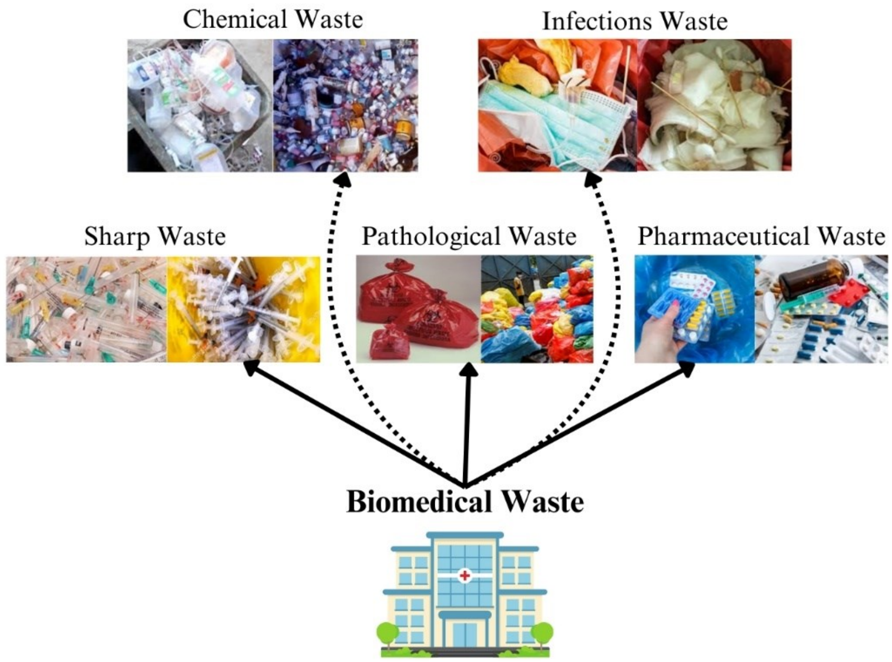


Figure 1: Image dataset

2.3. Proposed method

An extensive overview of the EnU-Net-DNN-TC framework is given in this section. This approach uses the EDN as its primary training unit and is inspired by the ideas of unsupervised feature learning. To create feature maps, the encoder phase combines pixel-wise tanh non-linearity, filter convolution, subsampling, and max-pooling. The decoder receives these high-level feature maps and uses aggregated learning variables to upsample them. Lastly, these upsampled maps are convolved to reconstitute the original picture.

2.4. Design of U-Net framework

Convolutional network design, or u-net, allows for quick and accurate picture segmentation. Strongly utilized for semantic segmentation tasks, especially in biological image analysis, is the U-Net framework. Its exact pixel-level classification is made possible by its encoder-decoder structure with skip connections, which is a design feature that has proved crucial to many medical imaging applications. Skip connections, which establish direct links between corresponding levels between the encoder and decoder, are one of U-Net's unique characteristics. These interfaces help with accurate object localization during segmentation by transferring feature maps from the encoder to the decoder. U-Net successfully preserves the fine-grained information required for precise segmentation by fusing upsampled features from the decoder with high-resolution features from the encoder. U-Net uses transposed convolutions, often referred to as deconvolutions, in the decoder portion of the network to upsample the feature maps. Figure 2 demonstrates the architecture of the U-Net.

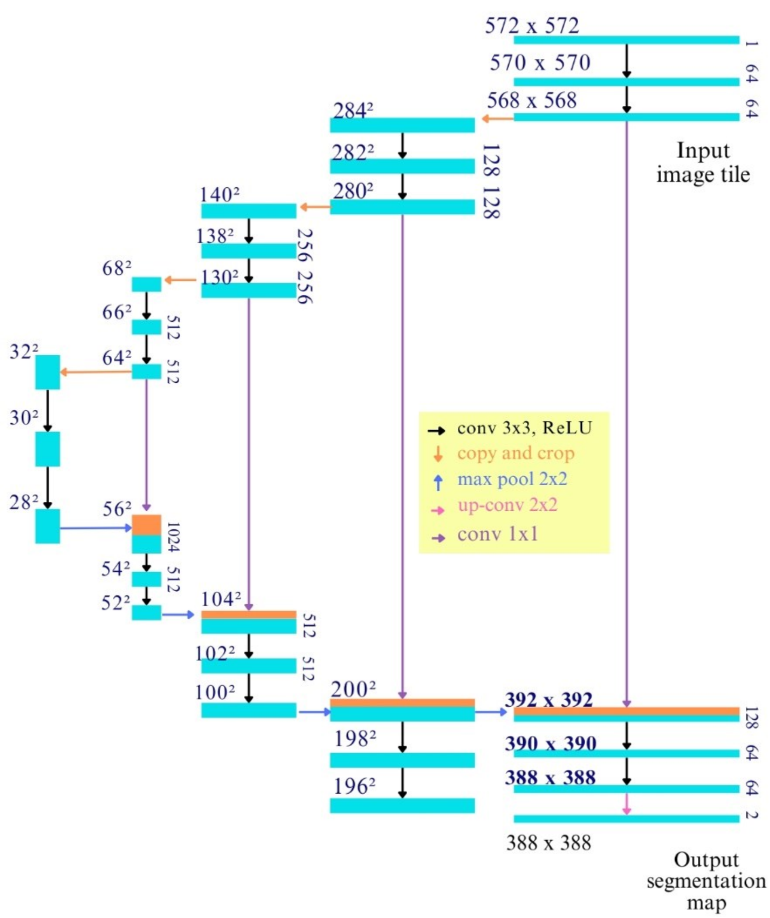


Figure 2: The architecture of the U-Net framework

This procedure intends to restore the spatial resolution that was lost during the encoder stage's downsampling. U-Net aligns with the original input size by gradually upsampling to recreate the segmented image with pixel-level accuracy. A pixel-wise classification layer, or softmax layer in the case of multi-class segmentation problems, is the last layer in the U-Net architecture. This layer divides the image into discrete areas according to learned features by assigning a probability distribution to every pixel within the specified classes. U-Net is renowned for its parameter efficiency, using fewer parameters than fully convolutional networks of comparable depth, yet having a deep architecture. Because of this feature, U-Net performs well on jobs requiring a lot of computational power or little training data, which is typical in medical imaging. Numerous biomedical imaging applications, including organ localization, tumor detection, and cell segmentation, have seen widespread application of U-Net. Researchers and practitioners in the healthcare field appreciate it because of its robust performance and ability to handle complex structures and different textures in medical images.

U-Net is essentially made up of two networks: an encoder network and a decoder network. The encoder employs convolutional and pooling layers to increase the depth of the input image while gradually decreasing its spatial dimensions, much like conventional convolutional neural networks (CNNs). High-level features are extracted from the input image through this technique, which captures both local and global context. The effectiveness of the U-Net framework in semantic segmentation tasks is demonstrated by its design, which makes use of an encoder-decoder architecture with skip connections and effective upsampling. This is especially important in biomedical imaging, where exact localization and accurate segmentation are critical. the design of the U- Net decoder is structured in Figure 3.

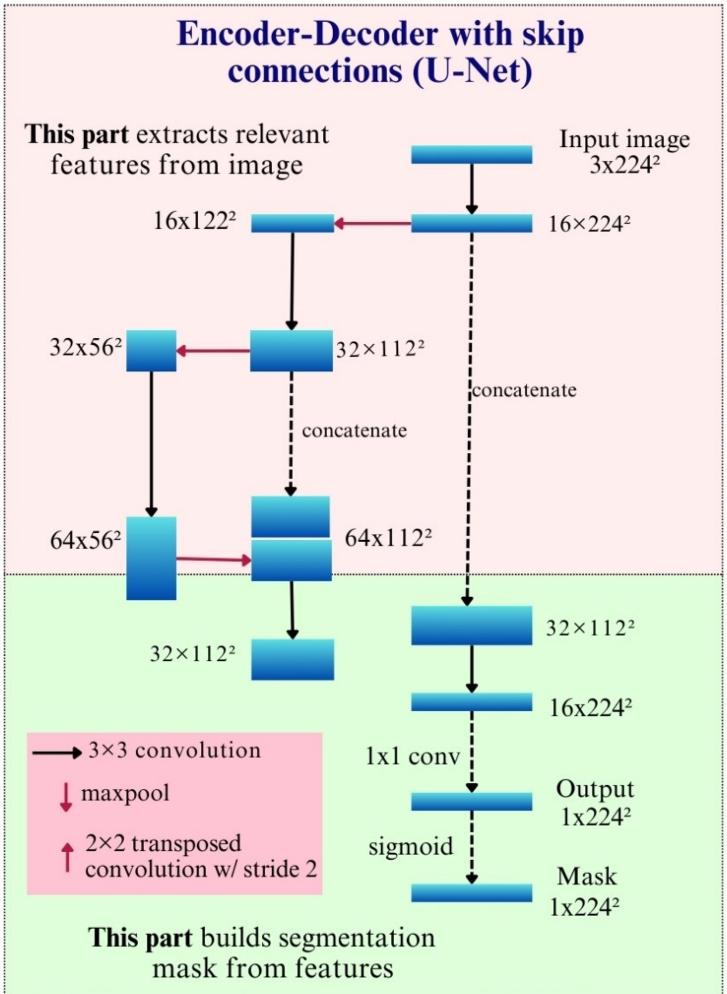


Figure 3: Design of UNet decoder

2.5. Application of CSS to the suggested EnU-Net framework

By using Content-Sensitive Sampling (CSS) to improve semantic segmentation, the EnU-Net system solves the problem of efficiently sampling pixels with different data densities in biomedical pictures. By dynamically modifying the sample rate in response to local image information, CSS enhances pixel sampling and increases segmentation accuracy across various locations of interest. With CSS, adaptive pixel sampling is made possible by integrating Bayesian uncertainty estimates into the U-Net architecture. By prioritizing regions with limited data, CSS ensures that the model focuses on underrepresented areas, enhancing its ability to learn from diverse examples. This approach mitigates biases that can arise from over-represented classes and improves overall model robustness. CSS works by analyzing content characteristics within the dataset to identify these sparse regions, allowing for targeted sampling that enriches the training process. This strategic emphasis not only optimizes the model's performance but also promotes a more balanced representation of the data, leading to improved segmentation and classification accuracy in complex scenarios. By incorporating CSS, the framework effectively enhances its learning capabilities, ultimately contributing to more reliable and precise outcomes in biomedical waste management. The goal of this methodological improvement is to save resources in less important portions of the image while allocating computational power to areas of the image that need finer segmentation information. The Bayesian Uncertainty Estimation equation (1-5) is as follows :

$$\sigma_i^2 - \mathbb{E}[(y_i - \hat{y}_i)^2] \tag{1}$$

Here, σ_i^2 represents the uncertainty associated with the pixel i in the segmentation output, where y_i is the ground truth and $\hat{y}_i$ is the predicted segmentation label.

$$p_i - \frac{1}{1+\exp\left(-\alpha \cdot \sigma_i\right)} \tag{2}$$

The sampling probability p_i adjusts based on the estimated uncertainty σ_i using a sigmoid function parameterized by α. Higher uncertainty leads to higher sampling probability.

$$\mathcal{L} - \mathcal{L}_{\mathrm{seg}} + \lambda\ {}_i p_i \cdot \mathcal{L}_{\mathrm{anx}}(x_i, y_i) \tag{3}$$

The total loss $\mathcal{L}$ combines segmentation loss $\mathcal{L}_{\mathrm{seg}}$ and auxiliary loss $\mathcal{L}_{\mathrm{anx}}$ weighted by the sampling probability p_i and a regularization parameter λ.

$$\text{Sampling Rate} - {}_i p_i \tag{4}$$

The sampling rate dynamically adjusts during training based on the computed sampling probabilities p_i across all pixels.

$$\theta_{\text{new}} - \theta_{\text{old}} - \eta \cdot \nabla_{\theta}\mathcal{L} \tag{5}$$

During optimization, where θ represents t ↓↓model parameters, updates are performed using the gradient $\nabla_{A}\mathcal{L}$ with a learning rate n.

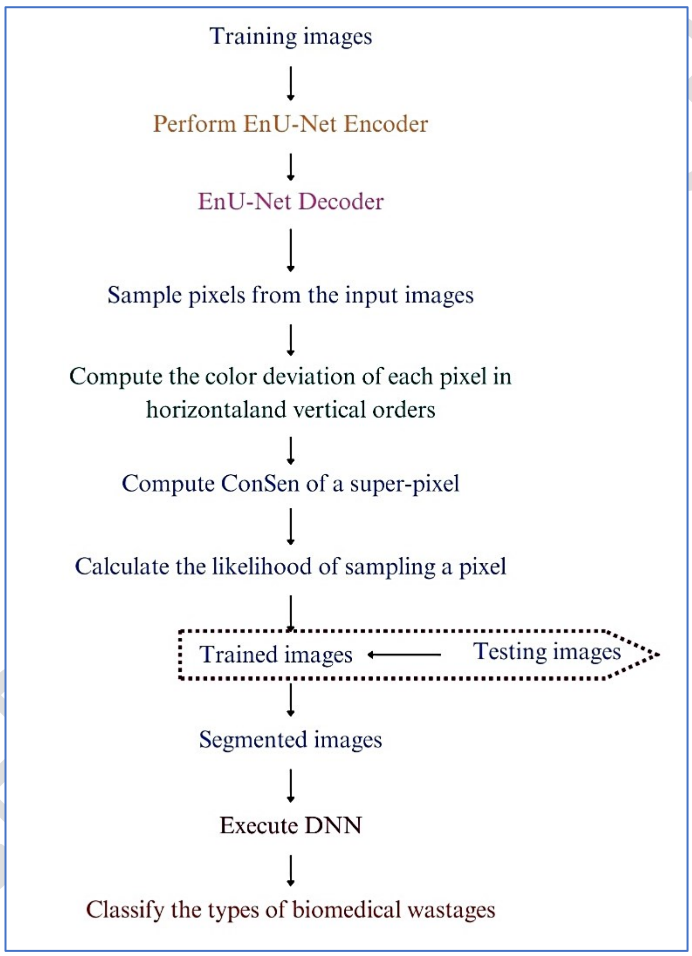


Figure 4: Flow diagram of EnU-Net-DNN-BMWC framework

By using Bayesian uncertainty estimates to dynamically modify pixel sampling rates during training, CSS improves the EnU-Net architecture. Through the use of a sigmoid function, the sampling probability pi is influenced by the uncertainty σi, which represents the model's level of confidence in each pixel prediction. Greater sampling probabilities are assigned to pixels with greater uncertainty, so resources are distributed more efficiently to areas where segmentation accuracy is critical. EnU-Net enhances segmentation accuracy across biological pictures by optimizing computing resources through the incorporation of CSS. By precisely identifying and classifying waste materials, this adaptive strategy not only improves model performance but also makes biomedical waste management more efficient.

Proposed algorithm

Input: Image set

Output: Classified biomedical wastage classes

Initialize;

for(each input image)

Perform the encoder of EnU-Net;

Execute the decoder of EnU-Net;

for(each pixel in image)

Calculate the color variation of each pixel;

Compute the likelihood of each pixel being sampled;

Sample pixels in the data-sparse regions;

end for

Train the EnU-Net in an end-to-end manner; obtain

the segmented images;

Apply DNN classifier;

Find the category of biomedical wastage;

end for

End

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3. Results

In this section, the comparison is carried out based on precision, recall, f-measure, accuracy, error rate, and Root Mean Squared Error (RMSE).

3.1. Accuracy

Figure 5 presents a comparative analysis of accuracy between DNN-BMWC and the proposed EnU-Net-DNN-BMWC across different numbers of images. The results show a consistent improvement in accuracy for EnU-Net-DNN-BMWC over DNN-BMWC at each increment of image count. Specifically, starting from 15 images, EnU-Net-DNN-BMWC achieves 82% accuracy compared to 80% for DNN-BMWC, and this trend continues with EnU-Net-DNN-BMWC consistently outperforming DNN-BMWC by 2% at each subsequent stage. By the time the dataset reaches 90 images, EnU-Net-DNN-BMWC achieves 92% accuracy, showcasing its superior performance in image classification tasks compared to the baseline DNN-BMWC model.

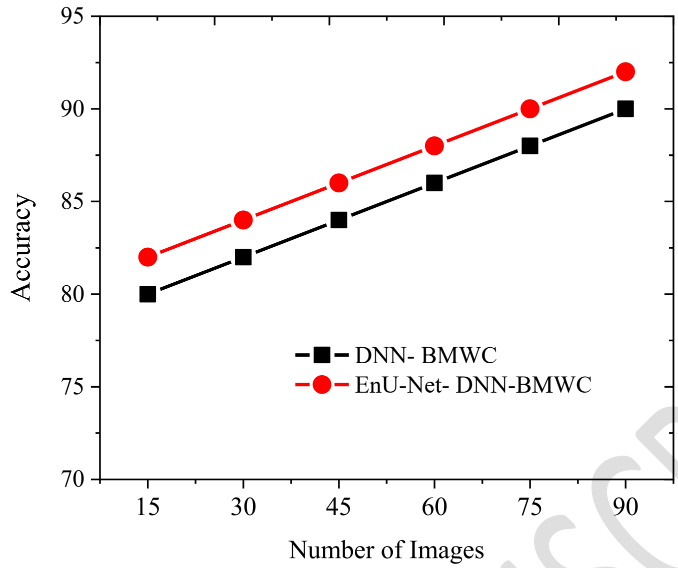

Figure 5: Comparison of DNN BMWC's Accuracy with the Proposed EnU-Net-DNN-BMWC

3.2. Precision

Figure 6 illustrates a comparative analysis of precision between DNN-BMWC and the proposed EnU-Net-DNN-BMWC across varying numbers of images. The data shows a consistent improvement in precision for EnU-Net-DNN-BMWC over DNN-BMWC as the number of images increases. Starting with 15 images, EnU-Net-DNN-BMWC achieves a precision of 0.83, compared to 0.8 for DNN-BMWC. This trend continues with EnU-Net-DNN-BMWC consistently surpassing DNN-BMWC by 0.03 to 0.04 precision points at each subsequent stage. By the time the dataset reaches 90 images, EnU-Net-DNN-BMWC achieves a precision of 0.93, demonstrating its superior performance in precision-oriented tasks compared to the baseline DNN-BMWC model.

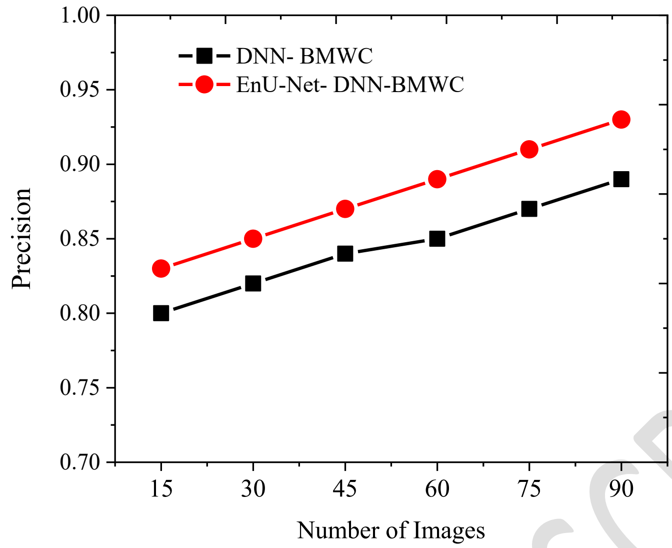

Figure 6. Precision Comparison of the proposed EnU-Net-DNN-BMWC and DNN BMWC

3.3. F-measure

Figure 7 depicts a comparative analysis of the F-measure between DNN-BMWC and the proposed EnU-Net-DNN-BMWC across varying numbers of images. The results consistently show that EnU-Net-DNN-BMWC outperforms DNN-BMWC in F-measure as the dataset size increases. Beginning with 15 images, EnU-Net-DNN-BMWC achieves an F-measure of 0.81, compared to 0.77 for DNN-BMWC. This performance gap widens with each increment in the number of images, with EnU-Net-DNN-BMWC consistently achieving higher F-measure scores than DNN-BMWC. By the time the dataset includes 90 images, EnU-Net-DNN-BMWC achieves an F-measure of 0.89, indicating its superior capability in achieving a balance between precision and recall compared to the baseline DNN-BMWC model

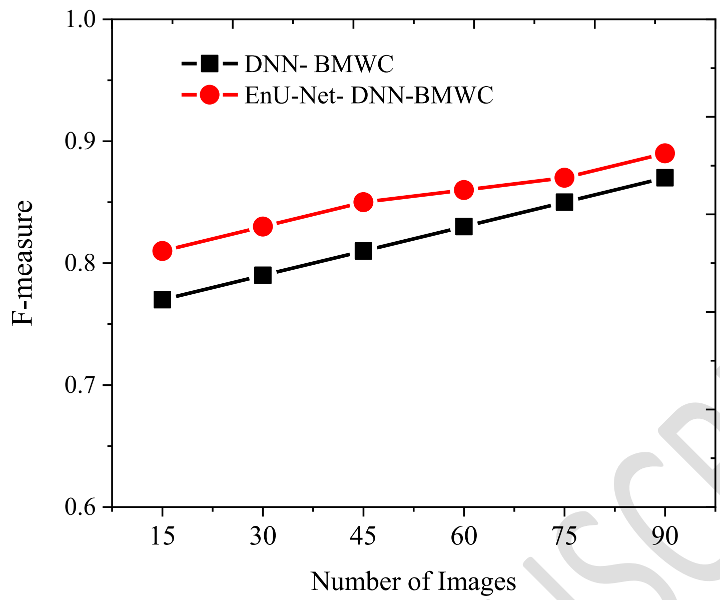

Figure 7: Comparing the F-measures of the proposed EnU-Net-DNN-BMWC with the DNN BMWC

3.4. Recall

Figure 8 presents a comparative analysis of recall between DNN-BMWC and the proposed EnU-Net-DNN-BMWC across varying numbers of images. The results consistently demonstrate that EnU-Net-DNN-BMWC achieves higher recall scores compared to DNN-BMWC as the dataset size increases. Beginning with 15 images, EnU-Net-DNN-BMWC achieves a recall of 0.8, while DNN-BMWC achieves 0.75. This performance gap continues to widen with each increment in the number of images, with EnU-Net-DNN-BMWC consistently achieving superior recall scores. By the time the dataset reaches 90 images, EnU-Net-DNN-BMWC achieves a recall of 0.98, highlighting its enhanced ability to correctly identify relevant instances compared to the baseline DNN-BMWC model

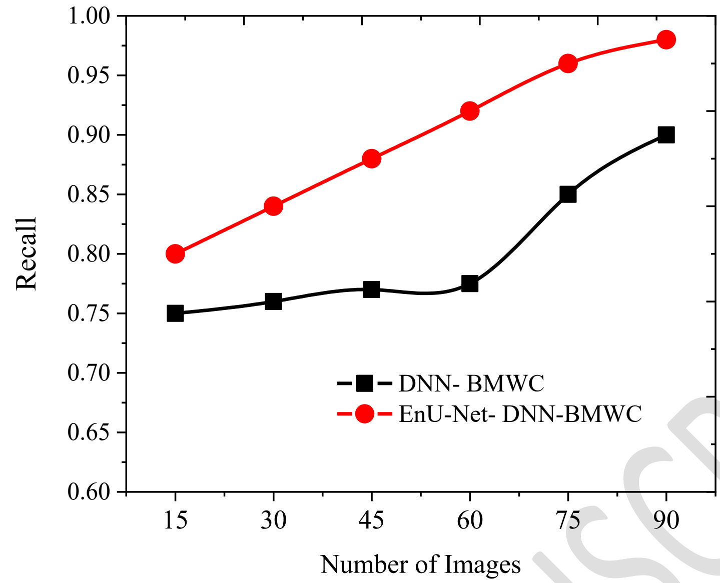

Figure 8. Comparing the proposed EnU-Net-DNN-BMWC with the recall of the DNN BMWC

3.5. Error rate

Figure 9 illustrates a comparative analysis of the error rate between DNN-BMWC and the proposed EnU-Net-DNN-BMWC across different numbers of images. The data consistently shows that EnU-Net-DNN-BMWC exhibits lower error rates compared to DNN-BMWC as the dataset size increases. Starting with 15 images, EnU-Net-DNN-BMWC achieves an error rate of 0.16, compared to 0.2 for DNN-BMWC. This trend continues with EnU-Net-DNN-BMWC consistently reducing its error rate by 0.01 to 0.05 for each subsequent increment in the number of images. By the time the dataset includes 90 images, EnU-Net-DNN-BMWC achieves an error rate of 0.11, demonstrating its superior performance in minimizing classification errors compared to the baseline DNN-BMWC model.

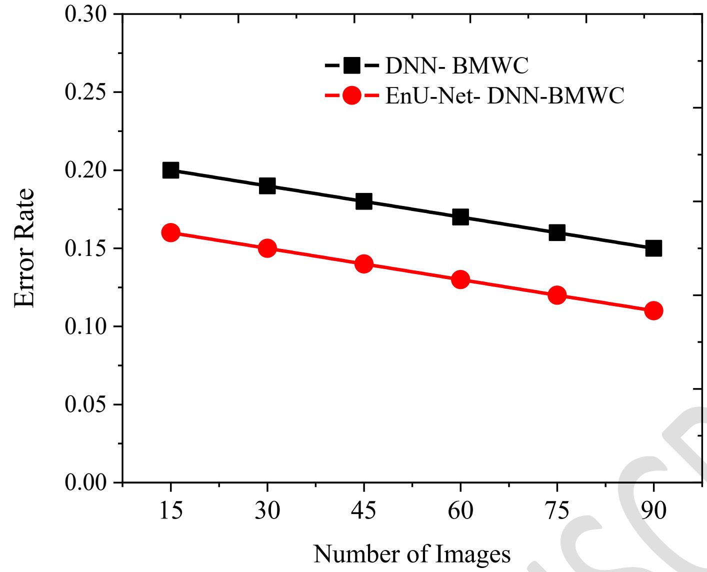

Figure 9: Error Rate Comparison between DNN BMWC and the Proposed EnU-Net-DNN-BMWC

3.6. RMSE

Figure 10 compares the Root Mean Square Error (RMSE) between DNN-BMWC and the proposed EnU-Net-DNN-BMWC across different numbers of images. The results consistently demonstrate that EnU-Net-DNN-BMWC achieves lower RMSE values compared to DNN-BMWC as the dataset size increases. Beginning with 15 images, EnU-Net-DNN-BMWC achieves an RMSE of 0.5, while DNN-BMWC has an RMSE of 0.55. This performance gap widens with each increment in the number of images, with EnU-Net-DNN-BMWC consistently reducing its RMSE by 0.02 to 0.07 for each subsequent stage. By the time the dataset reaches 90 images, EnU-Net-DNN-BMWC achieves an RMSE of 0.38, indicating its superior accuracy in predicting values compared to the baseline DNN-BMWC model.

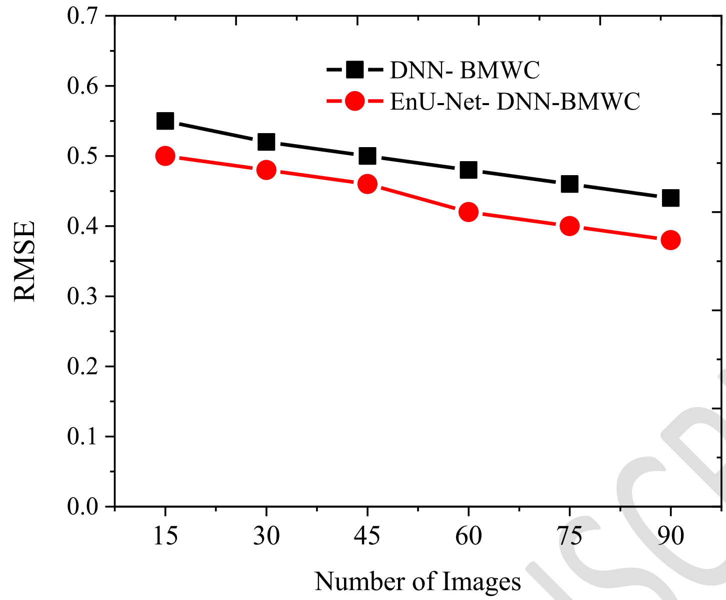

Figure 10: Comparing the Proposed EnU-Net-DNN-BMWC with the RMSE of DNN BMWC

EnU-Net-DNN-BMWC framework segmented pictures are shown in Figure 11 together with example pairs of original photos. Each pair provides visual evidence of how well the framework segments things in the photos. When compared to the segmented photos, which show the exact borders and classifications that the EnU-Net-DNN-BMWC model accomplished, the original photographs display a range of complexity and richness, from basic to detailed scenarios.

This graphic comparison highlights how the framework may improve picture segmentation tasks by using its sophisticated architecture, which combines improved feature learning and segmentation capabilities to provide accurate and dependable segmentation outputs on a variety of image datasets.

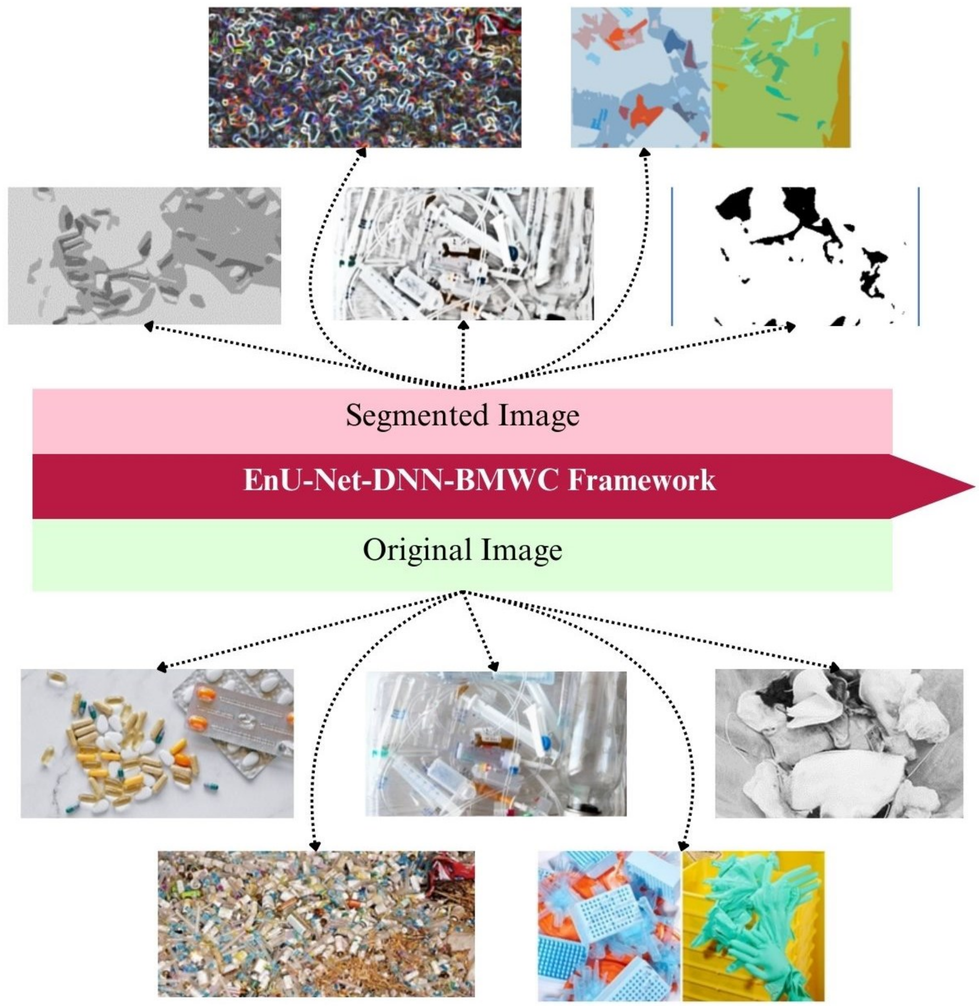

Figure 11: Original and segmented picture samples for the EnU-Net-DNN-BMWC Framework

4. Discussion

The comparative analysis of the EnU-Net-DNN-BMWC framework against the baseline DNN-BMWC model demonstrates significant enhancements across various performance metrics, underscoring the effectiveness of the proposed architecture in biomedical waste classification. The consistent improvement in accuracy, precision, recall, F-measure, and reduced error rates and RMSE values highlights the robustness of the EnU-Net-DNN-BMWC approach.

Starting with a modest dataset, the EnU-Net-DNN-BMWC achieves notable advancements in all metrics as the number of images increases. This trend indicates that the enhanced segmentation capabilities of the U-Net architecture effectively feed the DNN, allowing it to leverage more precise input for classification tasks. For instance, the significant gain in recall, culminating in an impressive score at larger dataset sizes, illustrates the model's superior ability to identify relevant instances accurately. Moreover, the lower error rates and RMSE values signify improved reliability in predictions, crucial for practical applications in biomedical waste management where misclassifications can have serious consequences.

The visual comparisons of segmented images further emphasize the framework's efficacy in delineating complex features, showcasing the model's ability to handle diverse scenarios and improve segmentation accuracy. This combination of quantitative and qualitative results positions the EnU-Net-DNN-BMWC as a formidable tool for automated biomedical waste classification, promising enhancements in operational efficiency and safety in waste management practices. Overall, the integration of advanced architectures within this framework offers a significant leap forward in the field.

5. Conclusion

To sum up, the ENU-NET-DNN-BMWC framework in this study represents a significant advancement in the field of biomedical waste management. Through rigorous experimentation and analysis, this study has demonstrated notable improvements in both segmentation accuracy and classification efficiency compared to conventional methods. By leveraging deep neural network architectures and tailored segmentation techniques, our framework not only enhances the precision of waste classification but also lays the groundwork for more effective and sustainable healthcare waste management practices. Moving forward, further refinements and integration with emerging technologies hold promise for extending these benefits to broader healthcare settings, thereby contributing to safer environments and improved public health outcomes globally. Based on the comparative analysis across different metrics—accuracy, precision, F-measure, recall, error rate, and RMSE—between DNN-BMWC and the proposed EnU-Net-DNN-BMWC framework, clear trends emerge.

1. EnU-Net-DNN-BMWC consistently outperforms DNN-BMWC in accuracy across varying dataset sizes. Starting from 15 images, EnU-Net-DNN-BMWC achieves 82% accuracy compared to 80% for DNN-BMWC, with a consistent 2% improvement maintained at each subsequent stage. By the conclusion at 90 images, EnU-Net-DNN-BMWC reaches 92% accuracy, underscoring its superior performance in image classification tasks.

2. The precision analysis reveals EnU-Net-DNN-BMWC's superiority over DNN-BMWC as the dataset size increases. Beginning at 15 images, EnU-Net-DNN-BMWC achieves a precision of 0.83, surpassing DNN-BMWC's 0.8. This lead widens to 0.93 by the time 90 images are processed, demonstrating EnU-Net-DNN-BMWC's enhanced precision-oriented capabilities.

3. EnU-Net-DNN-BMWC consistently achieves higher F-measure scores than DNN-BMWC across all dataset sizes. Starting at 15 images with an F-measure of 0.81 compared to DNN-BMWC's 0.77, the gap increases with each increment. By 90 images, EnU-Net-DNN-BMWC attains an F-measure of 0.89, showcasing its ability to balance precision and recall effectively.

4. EnU-Net-DNN-BMWC consistently outperforms DNN-BMWC in recall scores as the dataset size expands. Starting at 15 images, EnU-Net-DNN-BMWC achieves a recall of 0.8 versus DNN-BMWC's 0.75, with the gap widening incrementally. By the conclusion at 90 images, EnU-Net-

DNN-BMWC achieves a recall of 0.98, highlighting its superior ability to correctly identify relevant instances.

5. The analysis indicates that EnU-Net-DNN-BMWC maintains lower error rates than DNN-BMWC across increasing dataset sizes. Starting at 15 images with an error rate of 0.16 compared to DNN-BMWC's 0.2, EnU-Net-DNN-BMWC consistently reduces its error rate by 0.01 to 0.05 at each subsequent stage. By 90 images, it achieves an error rate of 0.11, showcasing its effectiveness in minimizing classification errors.

6. EnU-Net-DNN-BMWC achieves lower RMSE values than DNN-BMWC as the dataset size grows. Beginning at 15 images with an RMSE of 0.5 compared to DNN-BMWC's 0.55, EnU-Net-DNN-BMWC consistently reduces its RMSE by 0.02 to 0.07 at each stage. By 90 images, it achieves an RMSE of 0.38, demonstrating its superior accuracy in predicting values.

Overall, the comprehensive evaluation across these metrics consistently demonstrates the superior performance of EnU-Net-DNN-BMWC over DNN-BMWC in biomedical waste segmentation and classification tasks, underscoring its potential for enhancing accuracy, precision, recall, error rates, and predictive capabilities across varying dataset sizes.

Abbreviation

BMW - Biomedical Waste

EnU-Net - Enhanced U-Network

EDN - Encoder-Decoder Network

CSS - Content-Sensitive

Kmch - Kovai Medical Center and Hospital

Competing interests

The authors declare that they have no competing interests.

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Authors' contribution

Author A: Led the research design and methodology, developed the EnU-Net architecture, and conducted the initial experiments. Author B: Implemented the DNN-BMWC framework, carried out the segmentation and classification tasks, and analyzed the experimental results. Author C: Managed data collection and preprocessing, assisted in the implementation of the EnU-Net-DNN-BMWC framework, and provided critical feedback on the manuscript.

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