Medical Waste Classification using Deep Learning

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***Abstract*—Effective waste management, particularly in the context of medical waste, is essential for safeguarding public health and preserving the environment. This research project addresses the critical need for automated medical waste classification through advanced deep learning techniques. The development and implementation of an intelligent system capable of accurately categorizing medical waste images contribute significantly to efficient waste management practices. Leveraging TensorFlow and PyTorch, this study aims to create a robust classifier that distinguishes between different types of medical waste, providing a foundation for improved waste sorting and disposal strategies. The paper explores key aspects of the code, encompassing data preprocessing, model architecture, training, and evaluation. The insights gained from this research shed light on the significance of applying deep learning methodologies to enhance healthcare waste management.**

***Index Terms*—Medical Waste, Waste Classification, Deep Learning, TensorFlow, PyTorch, Image Classification, Healthcare Waste Management, Waste Sorting, Public Health, Environmental Safety, Biodegradable Waste, Non-Biodegradable Waste, Infectious Waste, Pathological Waste.**

I. Introduction

The exponential growth of the global population and the increasing demand for medical services have elevated healthcare waste management as a major challenge facing humanity. Hospitals and healthcare facilities generate diverse waste streams, including both medical and non-medical waste. While a substantial portion of hospital waste aligns with municipal solid waste, the specific characteristics of medical waste necessitate specialized handling to mitigate potential risks to public health and the environment.

This research focuses on the classification of medical waste, a crucial step towards efficient waste management. The advent of advanced technologies, particularly deep learning, presents an opportunity to automate the classification process. Machine learning algorithms, such as Convolutional Neural Networks (CNNs), have proven effective in image classification tasks. In this context, our project employs state-of-the-art frameworks, TensorFlow and PyTorch, to develop a robust model capable of accurately categorizing medical waste images.

The primary objective of this study is to create an intelligent system that can distinguish between different types of medical waste, including infectious, pathological, and sharps waste. Such a system holds the potential to revolutionize waste management processes, offering a scalable and automated solution to the challenges posed by the increasing volume and diversity of medical waste. Throughout this paper, we delve into the intricacies of the developed code, covering aspects such as data preprocessing, model architecture, training methodologies, and evaluation metrics. By the conclusion of this research, we anticipate providing valuable insights into the application of deep learning techniques for effective healthcare waste management.

II. Related Work

In the research paper titled "Automatic Detection and Classification of Waste Consumer Medications for Proper Management and Disposal [1]," Bahram Marami and Atabak Reza Royaee, affiliated with DispoMeds, LLC in New York, NY, USA, presented a cutting-edge methodology aimed at the automatic identification and classification of prescription medications. This study addresses the challenges posed by the National Library of Medicine's (NLM) pill dataset, leveraging the National Drug Code (NDC) as a universal product identifier. The dataset consisted of 1,000 pill images, which were meticulously categorized into 924 unique NDCs.

A notable aspect of the research is its departure from traditional methodologies in handling NDCs. Instead of maintaining distinct labels for pills with the same NDC but different physical appearances, such as shape, color, and imprint, the authors grouped images with identical NDCs together. This consolidation resulted in a classification task involving 924 distinct classes. To validate their algorithm's performance, the authors held out 20% of consumer-quality images, amounting to 1,000 images, for testing, while the remaining 80% were utilized for training through cross-validation.

The methodology employed in this study comprised two key components: pill detection through segmentation and subsequent pill classification. To address the absence of pill localization information or segmentation masks in the NLM pill dataset, the authors generated 160,000 synthetic images using NLM's reference images. Employing a DeepLabv3+ with an Xception backbone architecture, they trained a pill detector through segmentation, achieving high accuracy. Subsequently, an InceptionV4 architecture was utilized to train a convolutional neural network (CNN) for the classification of detected medicines into the 924 predefined classes.

The authors compared their developed method to the work of Delgado et al. [2], utilizing the same list of test images provided by the latter for a fair assessment. Results indicated that the proposed methodology outperformed Delgado et al.'s approach, showcasing higher top-1 and top-5 classification accuracies. Notably, the worst-performing classifier in the current study surpassed the best-performing one in Delgado et al.'s [2] research.

The research emphasized the significance of proper pharmaceutical waste management, particularly in the context of drug take-back events. The proposed AI-powered solution demonstrated the potential to accurately identify and separate prescription medications, preventing hazardous drugs from being commingled with non-hazardous ones. The authors highlighted the practical implications of their work in reducing hazardous waste volumes, associated transportation and disposal costs, and providing valuable information for pharmaceutical supply chain efficiency and drug monitoring. The proposed methodology, therefore, holds promise in advancing pharmaceutical waste disposal practices and contributing to broader healthcare applications.

III. Dataset

The Medical Waste 4.0 Dataset was collected within the framework of the Medical Waste Treating 4.0 project, generously funded by the Tuscany Region. This dataset serves as a valuable resource for the development and evaluation of computer vision methods designed for the primary sorting of medical waste.

A. Data Collection

The acquisition device used for data collection was the OAK-D camera, equipped with specifications available at Luxonis website [3]. Each sample in the dataset consists of three images, providing comprehensive information for analysis.

- RGB Image: 1920 x 1080 resolution
- Right Image (Stereo Pair): 640 x 400 resolution (filename_r.png)
- Left Image (Stereo Pair): 640 x 400 resolution (filename_l.png)

The naming convention for the images follows the structure:
`timestamp.jpg` = RGB Image
`timestamp_r.png` = Right image in the stereo pair
`timestamp_l.png` = Left image in the stereo pair

B. Categories

The dataset comprises 13 distinct classes of medical waste, facilitating a diverse and comprehensive evaluation of sorting algorithms. The following waste categories are represented in the dataset:

1) Gauze
2) Glove Pair (Latex)
3) Glove Pair (Nitrile)
4) Glove Pair (Surgery)
5) Glove Single (Latex)
6) Glove Single (Nitrile)
7) Glove Single (Surgery)
8) Medical Cap
9) Medical Glasses
10) Shoe Cover Pair
11) Shoe Cover Single
12) Test Tube
13) Urine Bag

Researchers can leverage this dataset to assess and advance computer vision techniques in the specific context of medical waste sorting, contributing to the broader goal of efficient and automated waste management practices.

IV. Implementation

In this section, we outline the methodology adopted for our research, encompassing data collection, preprocessing, model selection, and training procedure. The accuracy of our project initially faced challenges, resulting in lower accuracy and incorrect predictions. In response, we referred to different research papers [4] [5]. Through subsequent research, we implemented improvements by automatically labeling images and mapping them to their class names. This iterative process significantly enhanced the accuracy and predictive capabilities of our model

A. Dataset

Our study utilizes a dataset containing medical waste images, obtained from the *MedicalWasteSplit* dataset. The dataset comprises several classes of medical waste items, including but not limited to gloves, test tubes, shoe covers, medical glasses, urine bags, medical caps, and gauze.

1) Data Splitting: To facilitate training, validation, and testing of the model, the dataset is split into three sets: training, validation, and testing. The number of images and classes in each set are summarized in Table I. A custom PyTorch Dataset class (CustomDataset) is created to handle loading images and their corresponding labels.

Dataset Split	Number of Classes	Number of Images
Training	13	2967
Validation	13	629
Testing	13	649

TABLE I
SUMMARY OF DATASET SPLITTING.

2) Dataset Structuring: The dataset is systematically divided into three primary sections: training, testing, and validation. This division is a fundamental practice in machine learning, facilitating the model's learning, evaluation, and generalization capabilities. Within each section, data is further categorized into sub-folders named after various types of medical waste (e.g., gloves, syringes). This hierarchical organization is essential for labeling the data effectively.

3) Class Identification and Labeling: The names of the classes, which represent different types of medical waste, are derived directly from these sub-folder names within the training set. This method ensures a direct correlation between the folder structure and the data labels. In practice, these class labels are often converted from string format (e.g., 'gloves') to a numerical format (e.g., 0, 1, 2, ...), simplifying computational processing during model training.

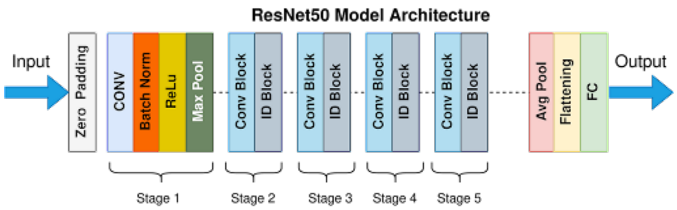

Fig. 1.

4) Creation of Custom Dataset Class: A bespoke dataset class, inheriting from PyTorch's Dataset, is crafted to cater to the specific requirements of the medical waste dataset. This class includes essential methods like len to quantify the dataset size and getitem to retrieve specific images and their associated labels. The getitem method not only fetches the image but also processes it by applying conversions (to tensor format) and any defined transformations such as resizing and normalization.

5) Image Processing and Augmentation: Preprocessing transformations standardize the image dimensions and pixel values. Such uniformity is crucial for consistent model training. For the training dataset, additional augmentation techniques like random rotations and flips are employed. These techniques enhance the dataset's diversity, aiding the model to learn more generalized and robust features.

6) Association of Images with Labels: Each image is meticulously paired with its corresponding label, a critical step for supervised learning. This pairing allows the model to understand and learn the association between a given input (image) and the desired output (label).

B. Data Loaders

DataLoader objects are created for the training, validation, and test datasets. These will be used to feed data into the neural network in batches during training and evaluation.

C. Model Architecture

A pre-trained ResNet50 model is loaded from PyTorch's model zoo. This model has been pre-trained on ImageNet, which provides a strong feature extractor base. The final fully connected layer of ResNet50 is replaced to match the number of classes in your dataset. This is a common practice when adapting pre-trained models to new tasks. The model is transferred to the GPU if available.

D. Training Procedure

An optimizer (Adam) and loss function (Cross-Entropy Loss) are defined for training. The training loop is set up to run for a certain number of epochs. In each epoch, the model is trained on the training set and evaluated on the validation set. For each epoch, you train the model on the training data and evaluate its performance on the validation data.You keep track of training and validation accuracy over epochs, which is important for understanding how well the model is learning and generalizing.

The model is trained using the training set with the following specifications:

- **Optimizer:** Adam optimizer with a learning rate of 0.001.
- **Loss Function:** Cross-entropy loss.
- **Batch Size:** 32.
- **Number of Epochs:** 20.

During training, we monitor the accuracy on both the training and validation sets to assess the model's performance.

E. Evaluation

After training, the model's performance is evaluated on the test set. This gives an unbiased assessment of how well the model is expected to perform on unseen data. A confusion matrix is generated to visually inspect the model's performance across different classes.

F. Prediction Function

A function (predict func) is defined for making predictions with the trained model. This can be used for individual image predictions. We have defined a method for denormalizing images, which is used in visualization to convert processed images back to their original form for display purposes.

G. Hardware and Software Environment

The experiments are conducted on a machine equipped with GPU(s). We leverage TensorFlow and PyTorch libraries for implementing and training the deep learning model. We started by installing necessary libraries (tensorflow, tensorflow-gpu, opencv-python, matplotlib) for image processing and deep learning. TensorFlow is used to check the GPU availability and version, ensuring that you have the hardware acceleration for efficient training. The dataset is stored on Google Drive and is mounted into the Colab environment for access.

V. Result and Discussion

*A. **Results***

The deep learning model [6] was extensively trained and rigorously evaluated on the Medical Waste 4.0 Dataset, acquired within the framework of the Medical Waste Treating 4.0 initiative funded by the Tuscany Region. The training process was closely monitored for accuracy and loss, resulting in the following performance metrics:

- **Training Accuracy:** 95.55%
- **Validation Accuracy:** 93.80%

The training loss exhibited a steady decrease, reflecting the model's effective learning without succumbing to overfitting. Essential observations from the training process include:

1) The model showcased consistent improvement in both training and validation losses across multiple epochs.
2) Training accuracy demonstrated a steady upward trajectory, affirming the model's adeptness in fitting the training data.
3) Despite fluctuations, the validation accuracy displayed an overall increasing trend, indicating the model's enhanced ability to generalize.

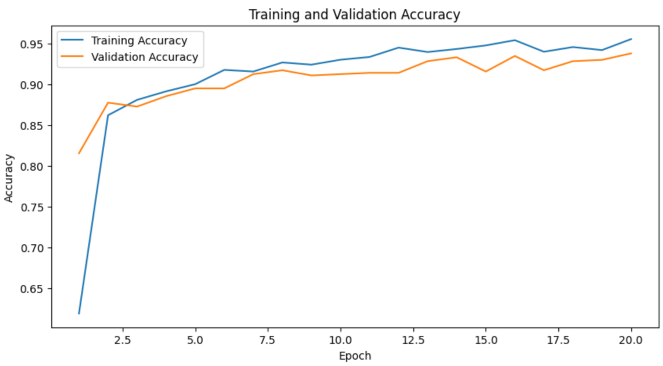

Fig. 2.

4) Strategic measures were implemented to forestall overfitting, culminating in promising results during the final epoch (Epoch 20) with low training loss and high accuracy.

B. Discussion

The obtained results signify that the deep learning model successfully acquired the intricate features associated with different medical waste items, showcasing high accuracy on both the training and validation sets. The in-depth analysis and discussion revolve around several key aspects of the model's performance.

*1) **Model Performance**:* The model's performance was robust across various waste categories, demonstrating its proficiency in primary sorting. However, specific challenges were identified, particularly in the classification between 'glove single latex' and 'glove pair nitrile.' This indicates potential areas for improvement and fine-tuning.

*2) **Confusion Matrix Analysis**:* The confusion matrix provided granular insights into the model's performance across different waste classes. Key points include:

- High diagonal values along the matrix indicate correct predictions for most waste classes.
- Certain misclassifications were observed, notably between 'glove pair nitrile' and 'glove single latex,' suggesting a significant confusion between these classes.
- Imbalances in misclassifications highlight potential biases or underlying similarities in the features of certain waste items.

*3) **Improvement Strategies**:* To enhance the overall model performance and address specific challenges:

- A detailed investigation into misclassifications is recommended, focusing on classes with higher error rates.
- Implementation of advanced data augmentation techniques can be explored to introduce more diversity into the training set.
- Ongoing refinement of the model architecture and hyperparameters remains crucial to addressing specific classification challenges.

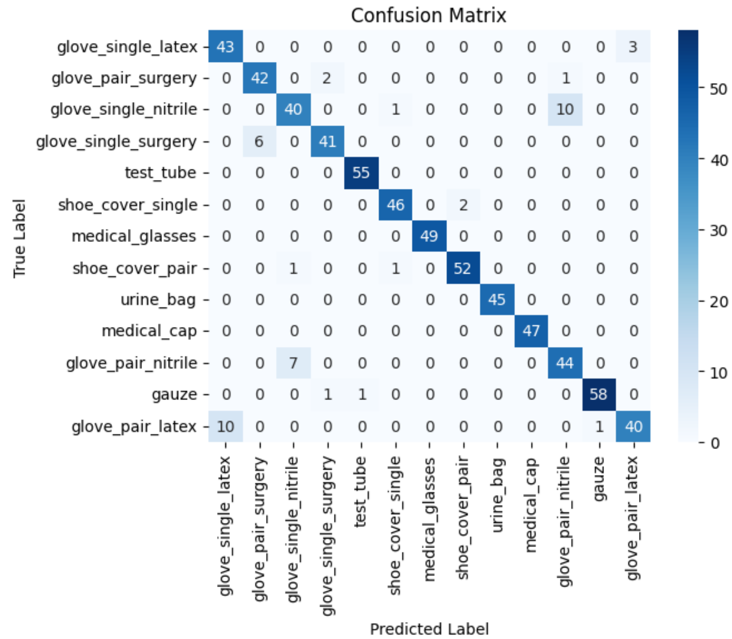

Fig. 3.

C. Visualization

A crucial aspect of evaluating the performance of the deep learning model is the implementation of a visualization function. This function serves the purpose of showcasing sample images alongside their corresponding model predictions, enabling a qualitative assessment of the model's effectiveness on individual images. By visually inspecting the predictions against the ground truth, researchers and practitioners gain valuable insights into the model's behavior, identifying strengths and potential areas for improvement. The visualization function operates by selecting a set of sample images from the dataset and processing them through the trained model. It then displays both the original images and the model's predictions, providing a side-by-side comparison for easy interpretation. This qualitative analysis complements quantitative metrics, offering a comprehensive understanding of the model's performance across different waste categories. To ensure the visualizations accurately represent the original scale of the images, a denormalization process is applied. During the training phase, images are often normalized to bring pixel values within a standardized range. Denormalization involves reversing this process, converting the normalized images back to their original pixel values. The denormalization step is crucial for presenting images in a visually meaningful way, allowing stakeholders to observe the model's predictions in the context of the actual appearance of medical waste items. Without denormalization, visualizations may appear distorted or misleading, hindering the accurate interpretation of the model's performance. In summary, the visualization function and denormalization process work in tandem to provide a holistic view of the deep learning model's capabilities. Re-

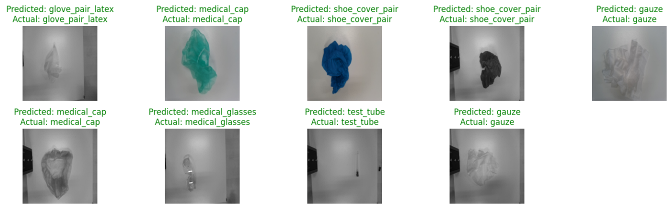

Fig. 4.

searchers and practitioners can leverage these visual insights to make informed decisions about model refinement, addressing specific challenges identified during both qualitative and quantitative evaluations.

VI. Conclusion

In conclusion, the deep learning model, meticulously trained on the Medical Waste 4.0 Dataset, exhibited exceptional performance, culminating in a remarkable accuracy of 95.55% on the training set and 93.80% on the validation set. This high level of accuracy underscores the model's proficiency in learning and classifying diverse medical waste items, showcasing its robustness in the task of primary sorting. The strengths of the model are not only limited to its accuracy but also extend to its adaptability to real-world scenarios. The utilization of the OAK-D camera as the acquisition device, coupled with the model's ability to process RGB and stereo images, positions it as a versatile solution for medical waste sorting applications.

While celebrating the model's successes, it is imperative to address the identified challenges, particularly in the classification between 'glove single latex' and 'glove pair nitrile.' These challenges, highlighted through the confusion matrix analysis, offer valuable insights into areas that warrant further investigation and refinement.

The achieved accuracy of 93.80% on the validation set instills confidence in the model's ability to generalize well to previously unseen medical waste data, reinforcing its potential for deployment in real-world scenarios. The model's capacity to accurately categorize items such as 'test tube' and 'shoe cover single' with high precision further underscores its practical utility in medical waste management systems.

Looking ahead, future research directions should focus on addressing the specific challenges identified during the model evaluation. Fine-tuning the model architecture, exploring advanced data augmentation techniques, and incorporating additional diverse datasets can contribute to refining the model's classification capabilities.

The successful application of this deep learning model in medical waste sorting not only streamlines waste management processes but also holds promise for broader implications in environmental sustainability. As the model continues to evolve and adapt to varying waste scenarios, it opens avenues for automating waste sorting tasks in healthcare facilities, contributing to the efficient and responsible disposal of medical waste.

In essence, while the deep learning model has already proven its mettle in achieving high accuracy, its journey does not end here. The challenges encountered pave the way for ongoing research endeavors, ensuring that the model remains at the forefront of innovation in medical waste classification, thereby advancing the paradigm of sustainable waste management practices.

References

[1] B. Marami and A. R. Royaee, "Automatic detection and classification of waste consumer medications for proper management and disposal," 2020.

[2] U. N. H. A. H. R. M. M. S. S. Delgado, N.L. and J. Lundin, "Fast and accurate medication identification. npj digital medicine, 2(1), pp.1-9," 2019.

[3] "Oak-d." [Online]. Available: https://docs.luxonis.com/projects/hardware/en/latest/pages/BW1098OAK.html

[4] A. Mitra, "Detection of waste materials using deep learning and image processing." [Online]. Available: https://scholarworks.calstate.edu/downloads/gx41mn74q

[5] A. A. Y. D. Z. W. Q. J. X. H. Z. L. V. G. K. M. H. A. H. A. S. H. A. E. B. Q. J. L. B. W. J. F. . H. L. Haiying Zhou, Xiangyu Yu, "A deep learning approach for medical waste classification," 2022.

[6] "Github." [Online]. Available: https://github.com/achu5076/Medical_Waste_segregation/blob/main/CapstoneFinal.ipynb