A Novel Approach for Waste Classification Using Active Deep Learning

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Abstract— Classification of waste on a large scale is complicated, making it difficult to sort and recycle the waste. Many existing systems use models like CNN and architectures such as ResNet, DenseNet, etc. These models perform well in waste classification, but the classification of waste remains complicated due to the inherent variability and ambiguity in waste images. Existing models may struggle with uncertain or ambiguous data, leading to misclassification and reduced overall accuracy. To address these challenges, combining active learning with deep learning can be beneficial. Active deep learning is a concept that improves the model by eliminating uncertainty about the data. This approach will enhance model performance and outperform existing systems. By developing a model for waste classification that combines ResNet50 and active learning, uncertainty and losses can be reduced, resulting in better performance compared to existing systems.

Keywords— *CNN,Resnet50,Active deep learning ,retraining ,Uncertain sample, labeled and unlabeled dataset, Active Learning, Deep Learning, Uncertainty, classification model, enhance model.*

I. INTRODUCTION

In Effective waste classification and recycling are critical in today's world, especially with the increasing volume of waste generated globally. To address this, various systems utilizing deep learning models like CNN with architectures such as ResNet and DenseNet have been developed for waste classification. Some of the existing systems include CGBNet, which helps identify green and brown compost accurately, even with limited labeled data, achieving an accuracy of 95%. This system is crucial for real-world automation [1]. GMC-MobileNetV3 is designed for classifying household waste. It is small, quick, and highly accurate, with an accuracy of 96.5%, making it suitable for compact devices [2]. WESNET is a small but efficient neural network used to sort and recycle waste more easily, classifying different types of garbage. This system is integrated into an intelligent trash bin with an app and management platform for real-time tracking [3]. RWC-Net is a model that can sort six types of waste categories, achieving an accuracy of 95.01%.

It combines features from DenseNet201 and MobileNetV2 [4]. The type-II fuzzy programming method for municipal waste management improves decision-making by handling uncertainty but requires integration with other methods to manage waste fluctuations [5]. Using a garbage image dataset, a CNN model is trained to automate the classification of garbage into five distinct classes [6]. A CNN model on the RetinaNet architecture, trained with the TACO Trash dataset using the PyTorch framework, has an accuracy of 80% in real-world environments [7]. Research conducted on the latest deep learning models for waste detection and classification provides information about many methodologies and datasets for waste classification [8].

Active learning is approach to create a high performance classifier with minimum size of training data. A subset of machine learning known as "active learning" allows a learning algorithm to interactively query a user to label data with the desired outputs. The algorithm actively chooses from the pool of unlabeled data the subset of examples to be labelled next in active learning. The basic idea behind the active learner algorithm concept is that if an ML algorithm could select the data it wants to learn from, it might be able to achieve a higher degree of accuracy with fewer training labels.this comes handy while traing with small amount of data and to annotate the unlabeled data more efficient and in less time .

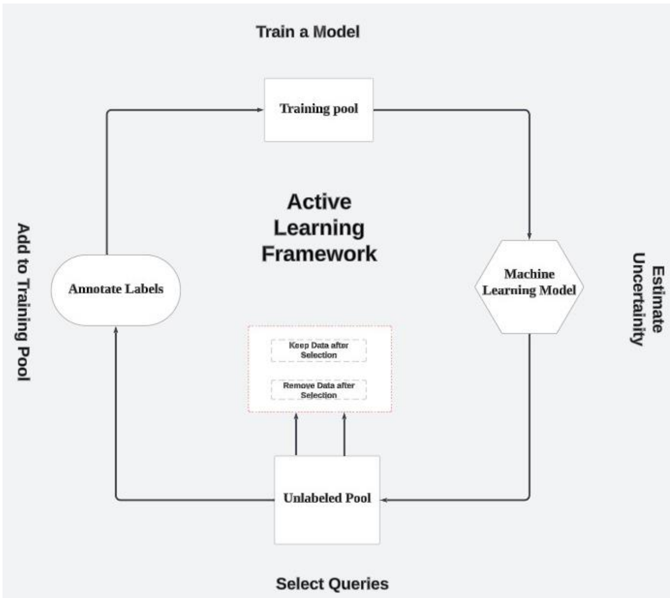

Figure 1:active learning block diagram

Integrating active learning with deep learning is challenging because ,Deep networks are overconfident They often give very confident but wrong predictions, Batch selection need to select many images at once, not just one, due to the computational cost of training deep models.application of these concept in real time application by monte carlo dropout for estimating uncertainity . the working of monte carlo dropout as followes. Monte Carlo Dropout simulates an ensemble of models using dropout at test time to estimate uncertainty., Randomly ignores some neurons during training to prevent overfitting, Apply dropout multiple times to get different model predictions, Use these to estimate uncertainty.

Even though all the models perform well in waste classification, they often face challenges such as data labeling, cost, model uncertainty, and performance limitations. To address these challenges, implementing active deep learning in waste classification models can rectify the issues. Some systems with active deep learning include electricity theft detection in smart grids and queuing for histological tissue classification. The electricity theft detection system selects the most important data for training using a combination of CNN and a Monte Carlo dropout method. [9]. Classifying tissue samples is key in medical analysis, which requires a lot of labeled data. ICAL, a new method, helps in learning from the most challenging and important data and ensures the model performs well across all tissue types. [10]. By combining ResNet-50 with active deep learning, a better-performing model than existing systems will be obtained, which will have a significant impact on waste detection and classification models.

Figure 2: sample image from each classes

II. Related work

In As mentioned before, Classification and sorting of waste in large scale is complicated, and there are many existing system for waste classification some of them are mentioned below. There is no existing active deep learning waste classification system for sorting and classification of waste. For reference Electricity theft detection approach with deep active learning and tissue classification are the two main references used for developing waste classification system with active deep learning.

Lipeng Zhu, .et.al [9] in their paper titled "Cost-effective data-driven electricity theft detection approach with deep active learning," introduced an innovative Intelligent Deep Active Learning (DAL) scheme that combines CNN learning with Monte Carlo dropout-based Bayesian active querying, offering a cost-effective solution for electricity theft detection.

Wentao Hu, Lianglun Cheng, Guoheng Huang[10] proposed a novel framework, "ICAL: Active Learning Framework for Histological Tissue Classification," which incorporates Incorrectness Negative Pre-training (INP) and Category-wise Curriculum Querying (CCQ) to enhance the accuracy of histological tissue classification.

Haruna ABDU, Mohd Halim Noor[8] presented a comprehensive survey titled "A survey on waste detection and classification using Deep learning," which discusses various image classification and object detection models, highlighting the DNNTC model for its high accuracy in waste classification tasks.

Suchisrit Gangopadhyay, Anthony Zhai [1] in their work, "CGBNet: A Deep learning framework for compost classification," introduced the CGB net model that leverages computer vision and transfer learning techniques to classify brown and green compost effectively.

Xueyong Tian..et.al.[2] developed an efficient algorithm, "Garbage classification algorithm based on improved mobile net V3," using a lightweight Mobile Net V3 architecture combined with CBAM (Convolutional Block Attention Module) and global average pooling, aimed at improving waste classification performance.

Jhandry R Lapo, Oscar M. Cumbicus Pineda[7] introduced a novel approach in their paper, "Detection of Recyclable Solid Waste Using CNN by Touch," where they developed a Retina Net model using PyTorch and ML Ops to accurately detect recyclable solid waste through tactile sensing.

Zhihu Yang and Dan Li [3] proposed a lightweight neural network-based system, "A neural network-based garbage collection management system," which employs the WasNet network to efficiently manage garbage collection processes.

MD Mosarrof Hossen [4] in his study, "A reliable and robust deep learning model for effective recyclable-based classification," introduced the RWC-Net model, designed to enhance interpretability and transparency in recyclable waste classification.

III. Proposed system

The Active Deep Learning is a approach that combine deep learning with active learning to make model training and performance better. This method uses a pre-trained ResNet50 model, enhanced with active learning techniques, to continuously improve its accuracy and efficiency for waste classification and sorting. Working as follow . First, we train the ResNet50 model on a set of labeled waste images. Once that’s done, active learning comes into play to find and label the most uncertain and informative samples from a pool of unlabeled data. We measure the model’s uncertainty using methods like Monte Carlo Dropout and entropy-based sampling, which help pinpoint the most tricky and unclear cases. These newly labeled samples are then added back into the training set, allowing the model to keep refining and enhancing its classification abilities.

A. Dataset:
The dataset consists of three subdivisions train, test, and validation datasets and consist of seven classes namely organic waste, medical waste, E-waste, plastic waste, Glass waste, Wood waste, Metal. The initial training set sets the stage for the model's performance assessment. The dataset is customized by extracting organic waste from the waste classification dataset and merging it with the Trashbox dataset, In Trashbox cardboard and paper are merged as wood waste and some addition wood data are attached too.

B. Data generator:
Data generator separate the dataset further such as Initial training dataset and pool data.

C. Labeled Data:
Data that is labeled, Classes and annotated and organized in simple well-structured are Labeled data. The data used for the initial trained and base dataset are Labeled data. The Initial Training data is used to train the base model.

D. Unlabeled Data:
Data that is not organized or well structure are unlabeled data. The unlabeled data is referred as pool which contains mix of rest of data apart from initial train data.

E. Resnet 50 Model:
A pre-trained ResNet50 model (figure 9) is used as the foundation for this classification task. It is known for its feature extraction capabilities and custom classification layers. Initially, the ResNet50 layers are kept frozen to preserve the features learned from the dataset. The model is trained on the initial dataset using standard techniques. abolishes baseline performance, with the model parameters optimized to minimize classification errors on the labeled dataset.

F. Monte Carlo Dropout:
The Monte Carlo Dropout approach generates a range of predictions for each sample, allowing for the calculation of uncertainty based on prediction variability. Dropout is applied multiple times during inference to create an ensemble of models.

$1/T * (\sum P(y \mid x, w\_t)) = 1/T * \sum(P\hat{}t\ c)$-----(1)

Entropy is computed from the predictions obtained through Monte Carlo Dropout (1). The samples exhibiting high entropy are identified as the most uncertain and selected for further labeling.

H=$1/T * \sum(P\hat{}t\ c)\ \log\ 〚(1/T * 〛 \sum(P\hat{}t\ c))$--(2)

G. Uncertainty Sampling:
The uncertain samples (2) are labeled and incorporated into the training dataset. By adding these samples, the model's learning process is refined.

H. Retraining:
With the updated labeled data, the model is retrained like a loop until it reaches the desired Loss rate, Loss rate should be as low as possible it can be achieved through retraining the model by measuring uncertainty and updating the model in loop.

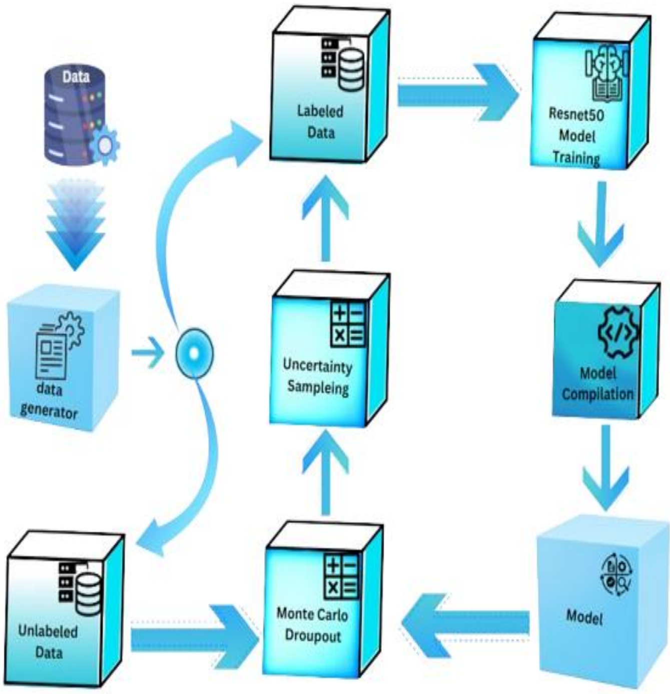

Figure 3:dataflow Diagram

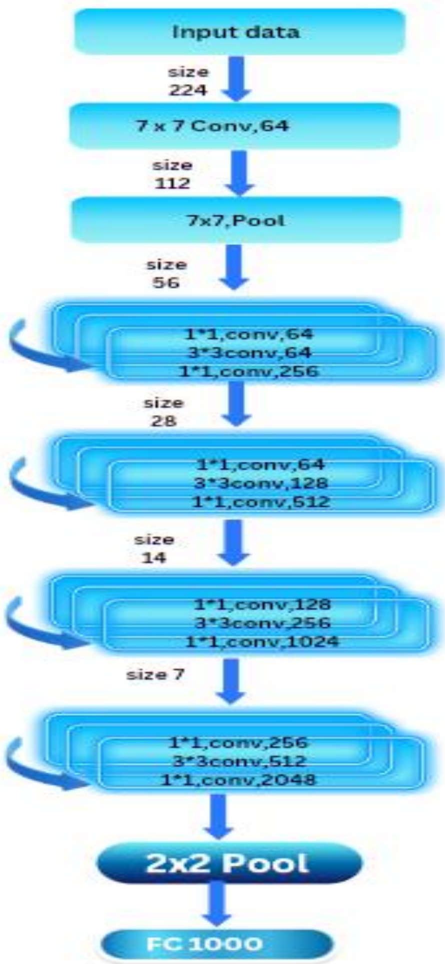

Figure 4:Resnet 50 Architecture

IV. Result and Discussions

This section talks about the methodology's findings. The F1 score, recall, accuracy, and precision for CNN, ResNet50, and Active Deep Learning (ADL) implemented ResNet50 are shown in Table 1. High performance is demonstrated by the Active Deep Learning ResNet50 model, which achieves 98.27% accuracy and 96.4% precision. This model performs better than every other model that was previously described; for a comparison with other models, see Table1.

Table 1:

Model	Accuracy	Precision	F1-score	Recall
CNN	59	61.8	63.6	65.5
Resnet50	85.71	90.9	88.5	86.1
CGBNet	95	92	92	91
GMCMobile net V3	96.5	96.89	96.55	96.24
RWC-net	95.01	95.04	95.01	95.01
ADL_Resnet	98.27	96.4	97.2	98.1

In comparison to the other models, ADL ResNet50 exhibits a higher accuracy, as indicated by the accuracy Figure 5 and (3). ADL ResNet50 outperforms all other analyzed models with a precision of 96%, as indicated by the precision figure. Based on these findings, it appears that Active Deep Learning ResNet50 outperforms other systems, offering a more dependable and accurate garbage categorization and sorting,model.

The total number of training samples is 27,431, the total number of validation samples is 2,336, and the total number of test samples is 2,238. The dataset used for training is a customized one.

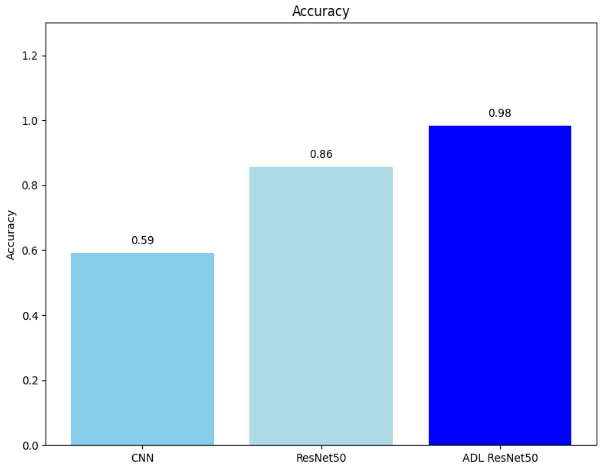

Figure 5: ADL_Resnet Accuracy

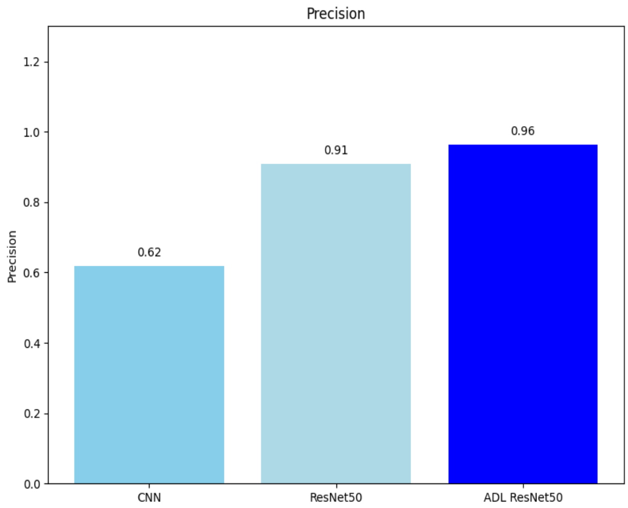

Figure 6: ADL_Resnet precision

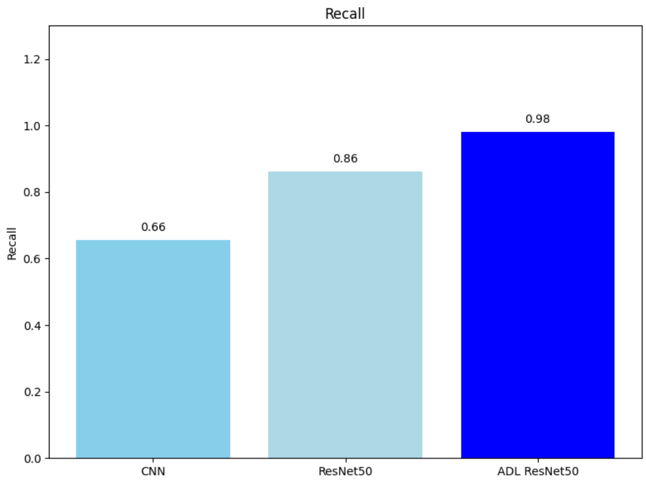

Figure 7: ADL_Resnet Recall

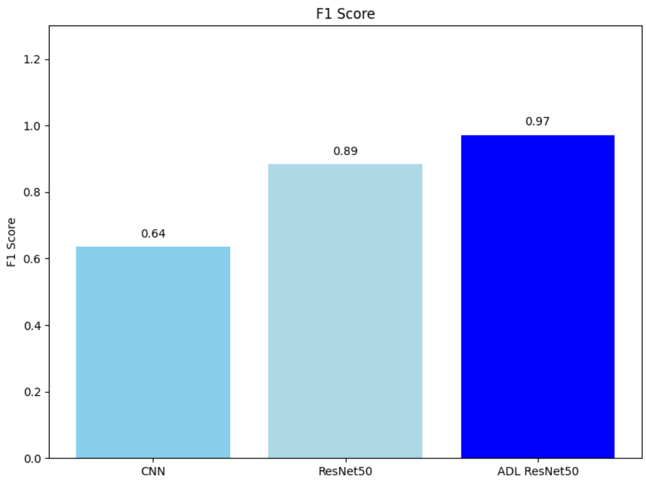

Figure 8: ADL_Resnet F1-Score

$$Accuracy(wc) = \frac{TP_{wc}+TN_{wc}}{TP_{wc}+TN_{wc}+FP_{wc}+FN_{wc}} \quad \text{---(3)}$$

$$Precision(wc) = \frac{TP_{wc}}{TP_{wc}+FP_{wc}} \quad \text{----}(4)$$

$$Recall(wc) = \frac{TP_{wc}}{TP_{wc}+FN_{wc}} \text{---------(5)}$$

$$F1score(wc) = 2 * \frac{precision(wc)*Recall(wc)}{Precision(wc)+recall(wc)} \text{-------(6)}$$

Where,

$TP_{wc} = True\ Positive$
$TN_{wc} = True\ Negative$
$FP_{wc} = False\ Positive$
$FN_{wc} = False\ Negative$

From refering all the Figure 5,6,7,8 its clear that by applying active learning in a deep learning model the performance increase is discovered. The difference is 10% which means the Active deep Learning Model has 10% higher accuracy,4% higher precision, 12% higher Recall,8% higher F1-Score refer to equation (3),(4),(5),(6) for better understanding of performance metrices .

V. Conclusion

There are many existing system models used to classify waste, which lag in some challenges like data labeling cost, performance limitations, and uncertainty. These challenges can be overcome by implementing the active deep learning concept. By implementing active deep learning in ResNet50, trained for waste classification with the TrashNet and waste classification datasets consisting of 27,000+ images, the result obtained consist an accuracy of 98.27% and a precision of 96%. This model outperforms existing systems and traditional methods. For future enhancement, this waste classification model can be trained with a larger dataset for better performance in a real-time environment.

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