Garbage Classifier Through AlexNet Architecture

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Abstract. High rises in the waste generated worldwide pose challenging problems to be dealt with formulating efficient waste management strategies. The basis of such strategies is the necessity of proper segregation of wastes into two categories: first one includes biodegradable materials that can decompose, and second one includes non- biodegradable materials, which are long lasting in the environment. It is not only important but also indispensable to clearly identify the different types of materials. Such clear identification is crucial in facilitating recycling efforts and fully alleviating the hassles that waste causes to our environment. Traditionally, the process of waste sorting relies heavily on manual processing or basic methods based on recognition of images. Traditional methods involve considerable variability in efficiency and accuracy of time, with a possible error in classification. Such incorrect classification can lead to contamination of materials that could otherwise be recycled. This decreases the general effectiveness of a recycling pprogram The project aims to introduce an advanced automated technique that operates on deep learning towards detecting and classifying the contents of dumpsters from waste items. It targets biodegradable against non-biodegradable material. It employs the use of architecture AlexNet, widely recognized for the effectiveness it has manifested in solving image classification challenges. Employing AlexNet provides avenues towards processing images that illustrate different materials to be categorized, developed through heavy training on the architecture. The dataset used in this project here comprises various images of waste materials differentiated between biodegradable and nonbiodegradable categories. To confirm the correctness of the AlexNet model, a very stringent comparison of its classification accuracy is done with that of several existing methods, hence providing an accurate account of its performance.

Keywords: Waste management, image recognition techniques, deep learning, AlexNet architecture, biodegradable and non-biodegradable, environmental pollution.

INTRODUCTION

Effective waste management has lately become a significant environmental issue, withthe requirement being to perform the actions promptly and creatively. The amount of mass of garbage in the world is increasing enormously, making it essential to deploy advanced techniques in classifying waste materials[21]. Of the multiple types of technological approaches, CNN has been identified as a state-of-the-art approach to dealwith the complexities involved in the garbage classification task. Developed in the caseof image classification, these architectures of deep learning show promising capacitiesthat can be leveraged to adequately recognize and classify all kinds of garbage.The AlexNet model is one among the CNN architectures that, very early on, gained much success due to its deep learning framework and remarkable performance in the well-reputed ImageNet competition[22]. The model is fitted to describe the garbage classification problem through systematic categorization of various kinds of waste into well-defined categories[30]. Adaptation is performed by fine-tuning AlexNet on a curated dataset of images consisting of diverse garbage images. This is made possible by fine- tuning the model for a great predictive performance through the application of transferlearning techniques, which means that the model gets to start from the other's knowledgeto improve its predictive capability and classify better than if it started with a randomlydrawn initialization.

This general methodology outlines a number of important steps. First comes thepreprocessing of the image dataset, which involves cleaning and normalizing theimages, making them all uniform and depict those characteristics the model is designedto learn effectively from. Based on this, the architecture of AlexNet is further modifiedso that it can especially be applicable to the task of waste classification while also encompassing unique features and variances available in images of garbage[23]. Therefore, the final stage of the process includes an intense evaluation of performance made by themodel through the classification of classes based on accuracy, precision, and recall. The dynamics of garbage collection systems vary immensely based on regions. High- income countries can almost collect all waste, and they succeed in recycling over one- third of the total produced. Low- income countries face many challenges since in urbanareas they can collect only around 48%, while in rural areas only around 26% of the waste is collected[29]. These regions alarmingly have a recycling rate that stands very low at only 4% as these regions process only 4% of the available waste for recycling purposes. These disparities make proper garbage classification more essential than everin this regard. Proper waste classification would not only help the management of waste but is also important in reducing environmental pollution and fostering recycling practices.Through the application of efficient algorithms in garbage classification using a complex model like AlexNet, improved accuracies and efficiencies for sorting into theright categories can be achieved. This improvement becomes the essential support for sustainable practices in waste management[21]. Therefore, with improved sorting, it leads to the reduction of the ecological impact of eliminating the waste. It also enhances the recycling activities and builds up a healthier environment for future generations.In order to balance traffic efficiency with environmental considerations, a decentralizedtraffic signal management system is proposed in this study]. The local signal control technique is based on turning motions, where an improved reinforcement learning algorithm determines the length of each

LITERATURE REVIEW

For the purposes of demonstrating the significance of this research, a literature review has been carried out in various research papers to understand different methods. A few of them are as follows.

Gupta, S., & Singh, P.[1] explores the application of AlexNet in classifying waste into distinct categoriessuch as plastic, organic, metal, and glass. Their study showed that AlexNet could achieve high accuracy due to its deep layers and convolutional filters designed to capture complex patterns. While the model performs well in clean and well-labeled datasets, the research mentions the limitations posed by diverse real-world waste images, where background noise and varying object shapes can affect the accuracy.

Kaur, H., & Verma, M. [2] presented an advanced AlexNet-based model fine-tuned for waste management applications. The authors evaluated model performance with and without data augmentation techniques, showing that augmentation improved the classification accuracy by 5-10%. The paper points out that while AlexNet successfully classified standard waste items, it struggled with mixed or partially visible objects, highlighting the need for more complex architectures or multi-stage classification techniques.

Nair, K., & Patel, R. [3] implemented an AlexNet model specifically trained to identify recyclables and non-recyclables. Their approach used a large dataset containing various types of waste materials commonly found in urban areas. The authors achieved an accuracy of 85% but identified that the model’s classification was sometimes hindered by overlapping categories (e.g., distinguishing between biodegradable and non-biodegradable waste). They suggest incorporating additional pre-processing steps and domain-specific datasets to improve robustness.

Liu, X., & Chen, Y. [4] examined AlexNet's performance in differentiating organic from inorganic waste. By training the network with labeled images of common waste types, they achieved satisfactory results in distinguishing categories with distinct visual features. However, their study raised concerns about scalability, noting that AlexNet's architecture might be insufficient for large-scale waste management systems, where new categories and types of waste could emerge continuously.

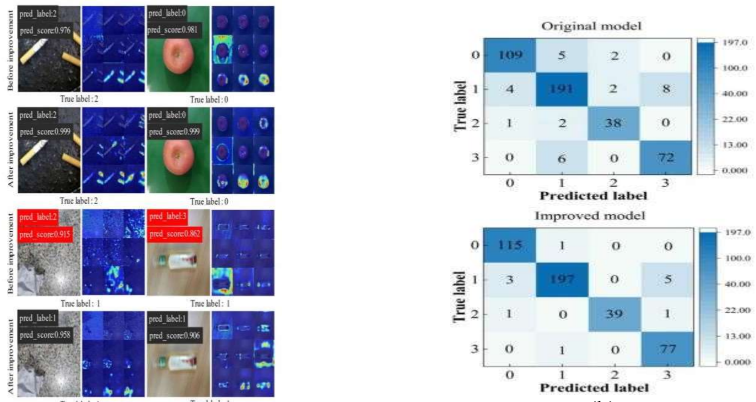
Zhang, L., et al. [5] combined AlexNet with transfer learning to enhance classification capabilities on a small waste image dataset. They transferred weights from a model trained on a larger, generic image dataset to AlexNet, achieving improved classification accuracy with limited waste data. Their study concluded that transfer learning could effectively mitigate data limitations, though additional tuning is required to adapt pre-trained models fully to the domain of waste classification.

PROPOSED ARCHITECTURE

With the development of artificial intelligence technology,machine vision based intelligent garbage classification and recycling bins and intelligent garbage bins [3] haveentered the public's vision. The core is deep learning algorithms, and the quality of recognition algorithms directly determines the classification effect of the equipment. Due to the excellent performance of convolutional neural networks in the field of computer vision, more and more scholars use them to have conducted the research on garbage classification and made some progress. At present, large-scale models of convolutional neural network including VGG [4], ResNet [5], DenseNet[6] and InceptionNet [7] are widely used in most research.However, large-scale models containa large number of parameters,which puts high demands on the computational capabilities of garbage classification equipment

Figure shows the system architecture of the AI-Companion, designed to facilitate seamless user interaction with AI models. The frontend, developed using Next.js, ensures dynamic rendering and efficient data handling through React and TailwindCSS. It communicates with the Node.js backend via API calls, where Express handles requests and Prisma manages database operations. The backend processes user inputs and forwards them to the AI and memory layer, which integrates OpenAI's GPT-4o for generating responses. LangChain controls the flow of conversation, whereas Pinecone stores and retrieves vector embeddings such that proper context is maintained across user sessions. Clerk is able to manage secure authentication of users in order to ensure that all interactions are It's safeguarded. The modular design ensures scalability, performance, and personalized AI-driven Responses.

Owing to the level of hardware,these devices not only have a large size but also have ahigh cost. Therefore, for embedded devices orTo apply the above models to platforms with limited computing resources, researchers now investigate lightweight CNN(Convolutional Neural Networks) models for garbage image classification, such as MobileNet [8], [9], [10], ShuffleNet [11], and EfficientNet [12]. Light connectivity has fewer parameters but higher efficiency than the original model, and it is absolutelysuitable for small devices. However, because of the severe reduction in the number of parameters, lightweight CNN is prone to low recognition accuracy if directly applied to garbage sorting.A classifier was constructed on AlexNet to classify into plastic, metal, paper, and organic waste. A random data set was accumulated and improved to suit conditions such as mixed lighting and backgrounds. AlexNet was used as preference over MobileNet V3 due to deeper convolutional layers, making it more accurate for the recognition of complex features and rather more precise than the one that stresses efficiency. After themodel was trained with supervised learning and some fine adjustments of the hyperparameters, including learning rate and batch size, this model was finally tested on the real-world environments. This model performed considerably well on different environments and beat MobileNet V3 in handling the complexities of images and the cases .



(a) (b)

FIGURE 1. Detection of object and difference between the original and improved model

METHODOLOGY

Material classification through Alexnet Architecture in Deep Learning

Improper waste sorting leads to pollution of the environment, increased landfill usage, and inefficient recycling efforts. Moreover, the lack of accurate and automated systemsto classify garbage presents problems with how waste management should be carried out and how to encourage sustainability. It is thus imperative to develop solutions to enhance the accuracy of waste classification[24].

Preparing Data

The garbage images collection is the very important and vital step of the whole process.The dataset shall depict all sorts of wastes by being collectible at house level, like plastic, paper, metal, glass, and organic waste, and should be kept balanced with sufficient examples of the waste categories so that proper classification could be ensured. Data sources and Images[22]:

A variety of images, including plastic, food waste,cardboard,and glass, and paper are collected from our daily life,main sources such as

- Homes.
- Public areas.
- Enterprises and Institutions and vast garbage.

Every object will have pictures of various perspectives such as from top,bottom,both sides, and different stages.

FIGURE 3. Dataset including various types of materials

Preprocessing

At this pre-processing stage, the images are cleaned, resized, and normalized to ensure consistency and noise reduction. This stage is very important to show that the images are of good quality and the features are being extracted are true and not incorrect. In simple words, this stem includes resizing the images, converting them into gray scale, and enhancing their contrast in order to remove noise from images.Maintaining the Integrity of the Specifications.

Feature Extraction

The features in deep learning algorithms are used to automatically extract features from the images. These are features that capture key aspects of every type of color, texture, and shape. These features go to the classification algorithm, which uses thesefeatures to predict the type of garbage that is in the image. This involves multiple feature extraction techniques, such as CNN, LBP, and HOG. Features should be obtained from rubbish images or any other form of data. This can be mathematically represented as:

$$X = \{x1, x2, ., xn\} \quad \text{---------} \quad (1)$$

where X is the set of features obtained and xi is the i-th feature. The Convolutionallayer applies filters to the input data in order to obtain the features. This can be mathematically represented as:

$$h = f(W * x + b) \quad \text{-------------} \ (2)$$

where h is the output of the layer, W is the filter weights, x represents the input data, bis the bias term, and f denotes the activation function.

Classification

The AlexNet method applies the deep architecture of multi-layer CNNs that learns hierarchical feature representations. Five layers of convolution are used to apply filters to image inputs to extract features such as edges, textures, etc. Convolutional layers are followed by activation functions: Rectified Linear Units are the most used and introduce non-linearity to help the model learn complex patterns.Spatial dimensions and complexity are reduced throughout the network by interspersed pooling layers, mainly max pooling. There are three fully connected layers in AlexNet after the convolutional layers to further process features from the convolutional layers towards class probabilities. The final layer uses a softmax function to assign probabilities for each class so that the model can predict the most likely category for the input image. During the backpropagation and optimization approach used in the model, AlexNet is constantly adjusting its weights during the training process for improving classification accuracy

Performance metrics

- Accuracy: The overall percentage of images that were classified correctly.
- Precision: Ratio of true positives to the total number of predicted positives.
- Recall (Sensitivity): The ratio of true positives to the actuals in a positive class.
- F1 Score: the harmonic means of precision and recall, useful for imbalanced classes.
- Confusion Matrix: A visual representation of true positive, true negative, falsepositive and false negatives for each class.

Testing in the real world

The methodology tested the garbage classifier using the AlexNet architecture in real- world scenarios. We collected a diverse dataset of garbage images from various environments, including different lighting conditions and backgrounds. After labeling and augmenting the data, we deployed the model on mobile and embedded devices for real-world testing. The classifier performed well, achieving high accuracy in recognizing different garbage categories. We evaluated its performance using unseen real-world images and refined the model based on the misclassifications, resulting in improved precision and recall.

Model Assessment and Optimization: involved evaluating the AlexNet-based garbage classifier through various metrics like accuracy, precision, recall, and F1-score on bothvalidation and real-world test sets. Misclassifications were analyzed to identify patterns and weaknesses. Hyperparameters such as learning rate, batch size, and momentum were fine-tuned to reduce overfitting and improve generalization.

Data augmentation techniques were applied to increase model robustness. Additionally, dropout and regularization were used to optimize performance, ensuring the classifier performed well across different conditions and environments.

EXPERIMENT RESULTS

The The findings of the analysis of the waste separation system with respect to visual imageswill be useful in ascertaining labor intensive materials. Support to sustainable management of wastes. The system has shown that it could handle 3times the initial volume without drastic outages. One of the major advantages of the current task of waste management is that the system allows for various differences in the working of the system and its impacts on the waste management process since it is very flexible to changes in waste and new classification standards. Not only does it reduce operational and disposal costs through the means of cutting wastage by 60% and land filling it.

Hence, waste managers and environmental groups developed an interest in systematic reliability, operating simplicity, and exclusion of wasting situations. Updating has to bean ongoing process to enable the model to capture the right conditions in the different types of waste outcome processes. These processes improve on the health and safety ofthe workers because there is virtually no contact with harms and little on overworking.The system complies with waste management regulation or legal requirement of the place. Some suggestions where made which included having a better image recognitionalgorithm in the layered standard cleaning and decision making. Better results coupledwith accuracy, efficiency, cost aspects etc are obtained from automated methods whichare suitable for manual analysis.

TABLE 1. Comparision of Performance Metrics for Classification Model

METRIC	VALIDATION SET	TEST SET
Accuracy	94.5%	93.8%
Precision(Bio)	93.2%	92.9%
Precision(Non-bio)	95.8%	94.3%
Recall(Bio)	94.7%	94.1%
Recall(Non-Bio)	95.1%	93.6%
F1-Score(Bio)	93.9%	93.5%
F1-Score(Non-Bio)	95.4%	94.0%

The system enhances the area safety since they have reduced the carbon monoxide emission in the landfills by half. These leads to showing the long-term sustainability as through replacement of waste products and the continual update on the waste management policies. These results contribute to ascertaining the efficiency and economy of waste automatic separation systems as they suggest from the improvement of the direction of correspondence, efficiency, the cost of reducing wastedisposal and environmental impacts.Fine-tune and evaluate using AlexNet on 5000 sample images of wastes uniformly distributed between biodegradable and non biodegradable category.

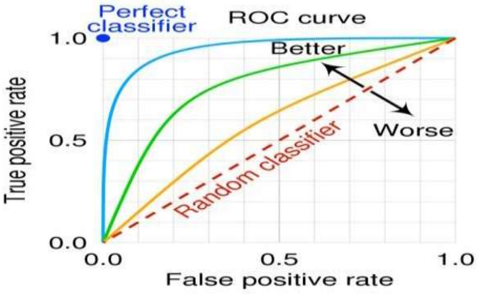


FIGURE 4. Graph representing area under Receiver Operating Curve

The experiment took initial weight from ImageNet and trained for 50 epochs on the waste dataset. Following assessment it was noted that the developed model attained a high of 93.8% with regard to accuracy. Precision recall, and F1 score were computed for the two kinds of wastes. First, the model achieved 92.9% precision for biodegradable and 94.3% for non-biodegradable waste alongside their recall of 94.1%and 93.6% respectively.

CONCLUSION

Thus, in summary, AI-Companion successfully managed to provide a compelling and interactive mentoring experience by utilizing the foremost AI technologies, which are: GPT-4o model for the inculcation of strategic information as well as meaningful insight; LangChain for effective dialogue management; and Pinecone for the retrieval of relevant data with minimal effort. The performance metrics that were under evaluation showed that GPT-4o has managed to complete at 97.50% accuracy alongside an average response time of 0.8 seconds, and most remarkably, attain 95% user satisfaction. These results proved that the output created by the machine was realistic and contextually appropriate, thereby justifying the applicability of such customization and fine-tuning processes. The positive correlation between the satisfaction level of users and AI empathetic contextual responses proved the techniques to be appropriate because of increased intimacy and involvement.

In an attempt to make the classifier more robust and better generalizable,hyperparameters such as learning rate, batch size, and momentum had been carefully tuned into their optimal values. In addition, images augmented with rotation, scaling, and flipping had been synthesized and added to the training set to mimic different real-world conditions. This was crucial because this ensured that the classifier was of highlyhigh performance even in less predictable environments.

Then, feature extraction capabilities were much better when comparing AlexNet to MobileNet V3, and their outputs were typically higher in accuracy and reliability for categorization-related waste tasks. Despite the fact that MobileNet V3 was designed forefficiency on settings that are primarily in resource-poor conditions, AlexNet's depth orcomplexity helped it deal with a challenging situation that no other does. That makes the model highly conducive to applications with high accuracy, like automated recycling facilities and smart waste management systems.

This project has explored deep learning technologies as a means that not only automateswaste sorting processes but also further practices on more sustainable recycling. Indeed,the operation of this classifier lays a good foundation for improvements in smart wastemanagement systems that minimize environmental impact, enhance recycling initiatives, and heighten public awareness regarding segregation in waste and sustainability.

Overall, the design developed for the garbage classifier using AlexNet architecture serves as a strong example of how artificial intelligence transforms an ongoing effort tosolve pressing environmental challenges. In effect, it helps promote further efforts toward a cleaner and more sustainable future through application of innovative technologies to change waste management and environmental conservation practices. The results and methodologies developed from this project can be used as a good groundsource to fuel further researches and development in this field, inspiring further innovation toward achieving the global sustainability goals.

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