Comparative Study of ML Algorithms for Garbage Classification

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Short Report

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Abstract

In today's world, the escalating waste crisis demands effective garbage classification strategies. As population growth and evolving needs contribute to unprecedented waste generation, repurposing items through recycling, reproduction, or reuse becomes imperative. Proper garbage classification is pivotal in realizing these goals. This paper presents a concise yet comprehensive comparative study of machine learning algorithms for garbage classification.

The primary objectives include comparing the performance of MobileNetV2, InceptionV3, and ResNet in garbage classification and scrutinizing optimal algorithms employed by researchers. The dataset comprises six garbage classes: cardboard, metal, paper, plastic, glass, and trash. Through rigorous evaluation, insights into algorithmic performance are presented. MobileNetV2 stands out, achieving a remarkable 94.48% accuracy on the validation set with minimal loss. InceptionV3 and ResNet50 yield accuracies of 86.08% and 88.54%, respectively. This study not only contributes to garbage classification knowledge but also highlights the real-world potential of the top-performing algorithm. As we address waste management complexities, this research signifies a step toward implementing efficient and accurate garbage classification systems for a sustainable future.

1. Introduction

In the contemporary world, the escalating global population and their ever-growing needs contribute to an unprecedented surge in daily garbage production. Amidst this waste, valuable materials like recyclable plastic or glass bottles and reusable metals can be harnessed for sustainable practices. The key to unlocking this potential lies in the accurate classification of garbage items. Trash classification has become a global concern due to heightened attention to environmental protection and resource efficiency [1]. The World Bank reports a staggering 4 billion tons of waste generated globally each year, with urban areas contributing significantly [2]. With the rapid economic development and increased living standards globally, garbage volume is expected to surge by 70% by 2050 [3]. Global garbage production is on the rise, particularly in developing countries, posing environmental and resource challenges [4]. Waste production is an inevitable outcome of population growth and economic development, leading to increased solid waste generation [5]. Annually, a substantial amount of municipal solid waste is generated globally, with improper management leading to severe environmental consequences [6]. Waste separation is crucial for addressing environmental problems, but the diversity of household waste complicates proper separation [8]. Waste, particularly plastic and rubber waste, poses a global challenge due to its slow decomposition [9]. Waste littering in urban areas is a significant concern, with projections indicating a substantial increase in municipal waste production [24]. The increase in population has led to a surge in waste volume, impacting areas and cities [25]. Waste classification and recycling play a crucial role in addressing the increasing volume of daily waste [26]. In recent years, the rapid development of deep learning technology has provided new solutions for garbage classification. Convolutional Neural Networks (CNNs) are widely used in image classification tasks, with researchers introducing improvements such as multi-feature fusion and attention mechanisms to enhance performance [27]. At present, there are some garbage classification methods based on deep learning. For example, the paper proposes a garbage classification method based on an improved VGG16 transfer learning model, aiming to improve the learning ability of a new field through information from related fields [28]. Several garbage classification approaches have been used in recent years, including artificial intelligence implementations and fuzzy approaches [29]. The paper investigates different models based on convolutional neural networks (CNNs) for garbage classification. The study aims to identify single objects in images and classify them into recycling categories, such as metal, paper, and plastic [30]. Garbage classification can reduce the waste of resources and enhance the recycling of garbage [31].

2. Significance of The Study

The study is important because it can address the urgent problem of increasing trash generation worldwide by creating a reliable and accurate rubbish classification system. Waste production rises in tandem with the world's population growth and rising levels of consumption. By facilitating the efficient recycling and reuse of materials, efficient rubbish classification can considerably lessen the total environmental impact of waste disposal and promote environmental sustainability. The study places a strong emphasis on finding and using valuable materials found in waste streams, such as reusable metals and recyclable plastic or glass bottles. Accurate waste classification enables the effective extraction of these resources, reducing the need for new raw materials and fostering the development of a circular economy. In the context of garbage categorization, the study assesses and contrasts the performance of three machine learning algorithms: MobileNetV2, InceptionV3, and ResNet50. This advances the fields of machine learning and artificial intelligence by demonstrating the ability of sophisticated algorithms to address environmental problems in the real world. According to the study, better performing algorithms like MobileNetV2 might be taken into consideration for real-time trash classification applications. Real-time garbage classification system implementation can improve waste management procedures and result in more environmentally friendly and sustainable practices. Precise trash classification facilitates improved waste management techniques, such as focused recycling initiatives. Consequently, this can help create a cleaner and healthier living environment by lowering the amount of waste dumped in landfills and the risks they pose to the environment.

3. Review of Related Studies

Sorting trash is a useful way to preserve the environment and make better use of available resources [1]. Recent years have seen notable progress in the field of intelligent waste classification, with an emphasis on utilising deep learning algorithms to improve accuracy and efficiency. To solve the difficulties in classifying waste items, researchers have investigated a variety of datasets, such as ImageNet, Cifar-10, MNIST, Huawei Garbage Classification Challenge Cup, "Huawei Cloud" datasets, Open-source image and trashNet dataset, and Kaggle.

Numerous techniques and strategies have been used in recent studies. Adedeji and Wang (2019) presented a convolutional neural network-based system that achieved 87% accuracy by using the Resnet50 algorithm and the ImageNet dataset [2]. Using the Cifar-10 and MNIST datasets, Kang et al. (2020) developed an autonomous garbage categorization system based on deep learning. They integrated various ResNet algorithms to achieve an overall accuracy of 99.96% with ResNet34-ALL [3]. Using the Huawei Garbage Classification Challenge Cup dataset, Fu et al. (2021) created a novel garbage classification system that integrates deep learning with an embedded Linux system. The system is applied to the algorithm GNet, which is based on MobileNetV3 and has an accuracy of 92.62% [4]. Using both "Huawei Cloud" datasets and real-world garbage samples, Jin et al. (2023) investigated a new deep learning-based machine vision system for garbage detection and classification using MobileNetV2 that obtained accuracy as high as 90.7% and 89.26% [4]. Alalibo and Nwazor (2023) used different epoch settings on ResNet50, inceptionV3, and an unidentified dataset to compare many convolutional neural network models. After 7 epoch resnet got validation accuracy of 92.06% and Inception got 91.59% acuuracy [5]. Masand et al. (2021) introduced ScrapNet, an efficient approach to trash classification, applying Modified EfficientNetB3 on an Opensource image dataset (Trashnet) that got 82.34mAp and 92.87 mAp[6]. Kumar et al. (2021) focused on an efficient classification of kitchen waste using VGGNet-16 on Kaggle dataset and got accuracy of 83% [7]. Yong, Liying, et al. (2023) did an efficient classification of kitchen waste using deep learning techniques. They used mobilenetv2 on an open-source crawl dataset and got an accuracy of 82.92% [8]. Girsang (2023) Classification Organic and Inorganic Waste with Convolutional Neural Network Using Deep Learning using mobilenet on Kaggle dataset ang got accuracy of 93.35%. Lin, K., Zhao, Y., Wang, L. et al. (2023) did a study on A visual deep machine learning method adopting transfer learning based upon ResNet50 for municipal solid waste sorting. Deep machine learning can help MSW sorting becoming into a smarter and more efficient mode The accuracy of ResNet50 on the MSW testing dataset was 88.50% and then improved, suggesting that ResNet50 model performs well in MSW classification [10]

4. Objectives of The Study

- To compare different image classification algorithms for garbage classification.
- To study and compare different optimal algorithms used by other researchers.

5. Proposed Work

5.1. Dataset

The performance of the model not only depends on the model used or fine-tuning of the parameters for a specific problem but also the data used. Researchers for various classification problems have used various datasets. Some used image datasets are trashnet, Huawei, Kaggle, cifar, mnist, or any opensource dataset. While others used self-created dataset of images from the internet. For our research problem, we used the dataset from Kaggle. The dataset consists of 2527 images of garbage which are classified into 6 classes [20]. The classes are cardboard, metal, glass, paper, plastic, and trash [23]. The size of each image is 512*384. The dataset is divided into training and testing sets and then fed to the models.

Link of dataset used: https://www.kaggle.com/datasets/asdasdasasdas/garbage-classification

Table.1. Number of images in each class

Classes	Number of images in each class
Cardboard	403
Glass	501
Metal	410
Paper	594
Plastic	482
Trash	137

The above table (table 1) shows the classes that are in the dataset that we used. There are 6 classes in the dataset cardboard, glass, metal, paper, plastic and trash.

The figure (Fig. 1) shows the different images of garbage within that class like there are images of cardboard boxes, plastic bottles, glass bottles, etc.

5.2. Research Methodology

In our investigation of garbage classification, we implemented state-of-the-art algorithms, namely MobileNet, ResNet50, and Inception. The selection of these algorithms was motivated by their widespread adoption and success in previous studies within the research community. Leveraging the experiences and positive outcomes reported by fellow researchers, we aimed to build upon a foundation of well-established methodologies.

To conduct our study, we acquired a comprehensive garbage dataset from Kaggle. Each image within this dataset maintains a standardized size of 512 by 384 pixels. The dataset underwent a meticulous partitioning process, resulting in the creation of distinct training and testing subsets. Subsequently, the chosen algorithms were subjected to training and evaluation procedures, utilizing the divided data to ensure robust model performance across varied scenarios.

5.2.1 Resnet50

We employed the ResNet-50 architecture for image classification, a deep neural network renowned for its effectiveness in computer vision tasks. ResNet-50 is composed of 50 layers [5], encompassing an initial convolutional layer (Conv1) for preprocessing input images. The architecture is characterized by the integration of residual blocks (Res2 to Res5), each consisting of convolutional layers, batch normalization, and skip connections. The skip connections, also known as shortcut connections, facilitate the flow of information through the network and mitigate the vanishing gradient problem. The final layer of the network is a fully connected layer (fc), modified in our implementation to align with the number of classes in the dataset. We based our model on the ResNet-50 architecture introduced by Kaiming He, et al., as detailed in the seminal paper 'Deep Residual Learning for Image Recognition' [34]. ResNet-50's depth and skip connections enable it to capture complex characteristics and hierarchical representations, which makes it a strong option for image classification problems.

5.2.2 MobileNet

MobileNet is used to demonstrate the model's flexibility and effectiveness in image classification tasks. The study methodology has been effectively incorporated with MobileNet, a lightweight convolutional neural network architecture, to tackle the difficulties associated with implementing deep learning models on devices with limited resources. The model, which was pre-trained on the ImageNet dataset, greatly reduces the computational load associated with typical convolutional layers by utilising depthwise [8] separable convolutions [9], a fundamental component of MobileNet. The code makes use of the MobileNetV2 variation, which provides a better, faster version. While its effective design guarantees a streamlined training procedure, MobileNet's placement within the overall architecture strategically aids in the extraction of relevant information from input photos. Pretrained MobileNet weights are used to capitalise on the model's good generalisation to a variety of datasets and to speed up convergence during training. Moreover, MobileNet integrates easily with well-known deep learning libraries like TensorFlow and Keras, demonstrating the adaptability and broad use of MobileNet in the machine learning field. This implementation's success confirms MobileNet's reputation as a potent image classification tool, especially when dealing with limited computational resources. This is reflected in the efficient use of MobileNet in the recycling material classification, as seen in the provided garbage classification.

5.2.3 InceptionV2

Developed by Google for picture classification tasks, InceptionV2, also referred to as GoogLeNetV2, is an extension of the original Inception architecture. It adds numerous enhancements in terms of computing performance and architectural design, building on the achievements of InceptionV1 (GoogLeNet). One of InceptionV2's primary objectives is to lower the computing cost without sacrificing accuracy. To improve model performance, the architecture makes use of methods like factorised convolutions, batch normalisation, and inception modules with extended filter banks.

The model creates different generators for training and validation sets and augments the data using the Keras ImageDataGenerator. For each classification task, it loads the underlying InceptionV3 model that has already been pre-trained on ImageNet [17], eliminates the top classification layer, and inserts custom layers. A GlobalAveragePooling2D layer, a Dropout layer [19] for regularisation, a dense hidden layer activated by ReLU, and a final output layer activated by softmax for multi-class classification are all included in the model. The Nadam optimizer and categorical cross-entropy loss function are used to construct the model. The value of 0.0001 is the learning rate. Training and validation data generators are used in conjunction with the fit generator function to train the model. During training, the top-performing model is saved using ModelCheckpoint. The model includes techniques like establishing a learning rate schedule, employing dropout for regularisation, and freezing the weights of the pre-trained base model. It also incorporates data augmentation methods to enhance the generalisation capacity of the model. The goal of these tactics is to prevent overfitting while yet obtaining high accuracy on the classification job. The InceptionV3 architecture is carefully considered during fine-tuning, and many callbacks are used to monitor and optimise the training process.

6. Experiment, Results, and Discussion

6.1. Experiment

We experimented the garbage classification model on google collab. The RAM is 12.7GB. The configuration of type of GPU used is Nvidia T4 Tensor Core GPU. First, we uploaded the dataset on the google drive. The drive was then connected to the current workspace or collab notebook. Then the dataset was loaded in the collab notebook. The dataset was then split into train and testing set. The model was built and trained using the train set. The model was tested using test set. The accuracy was then calculated and displayed.

6.2. Experiment Results

We have reviewed various research papers, and then we selected the algorithms that got accuracy above 90% (resnet50, mobilenet, inceptionv2). And for this study in spite of considering other performance metrics we have considered only accuracy metrics, which is most commonly chosen by other researchers.

Evaluation Metrics (Accuracy): Accuracy serves as a metric assessing the efficacy of a Machine Learning model in correctly predicting outcomes or labels for new data. Typically presented as a percentage or fraction, it signifies the proportion of accurate predictions relative to the total number of predictions made. The significance of accuracy lies in its reflection of the model's reliability and utility for the specified problem statement and stakeholders.

Accuracy = (number of correct predictions) / (total number of predictions)

or

Accuracy = (True Positives + True Negatives) / (True Positives + True Negatives + False Positives + False Negatives)

The results of our study are presented in Table 2, showcasing the algorithm names, dataset names along with garbage classes, and the corresponding results. The table also includes references to research papers that utilized similar algorithms. Notably, our findings indicate that during training, MobileNetV2 outperforms other algorithms, achieving a remarkable accuracy of 100%. Subsequently, during testing, MobileNetV2 maintains a high accuracy of 95.17%. ResNet50, on the other hand, exhibits a testing accuracy of 95.27%. Inception demonstrates impressive testing accuracy at 96.88%, coupled with a training accuracy of 86.08%. In summary, the test results for all algorithms exceed 90%, suggesting their effectiveness in accurately classifying garbage.

Table 2
Results of Proposed Algorithm

Sr. No.	Name of Algorithm	Dataset source	Classes	Result	Other Researcher used the same algorithm
1	Resnet50	Kaggle	Cardboard, Metal, Glass, Plastic, Paper, Trash	Test: 95.27%	[5] [10] [11] [18] [19] [20] [21] [23]
2	MobilenetV2	Kaggle	Cardboard, Metal, Glass, Plastic, Paper, Trash	Test: 95.17% Train: 100%	[4] [8] [9]
3	Inception	Kaggle	Cardboard, Metal, Glass, Plastic, Paper, Trash	Test: 96.88% Train: 86.08%	[17] [23]

Table 3 displays the algorithm names and associated dataset names utilized by researchers in their studies, showcasing the algorithms that yielded the best results. Consequently, we have selected these algorithms for our own study, given their consistent success in research conducted between 2020 and 2023. Notably, ResNet, MobileNet, and Inception stand out as the most frequently chosen algorithms across these studies. Also, the classes in the datasets are quite similar. Importantly, the overall accuracy of ResNet, MobileNet, and Inception consistently exceeds 90%, indicating their efficacy in various classification tasks.

Table 3
Algorithms used by other Researchers.

Sr. No.	Name of algorithms	Dataset	classes	Algorithm Outperformed	Acc. Of algorithm outperformed	Reference
1	Gnet based on Mobilenet	Huawei	hazardous waste, kitchen waste, residual waste and recyclable waste	Gnet	92.62%	[4]
2	Resnet50	trashnet (2527 images same classes)	paper, plastic, glass, cardboard, metal, and general trash	Resnet	92.06% val. Acc.	[5]
3	Mobilenetv2	opensource	recyclable waste, kitchen waste, hazardous waste and other waste	Mobilenet	82.92%	[8]
4	Mobilenet	kaggle	Organic and inorganic waste	mobilenet	93.35%	[9]
5	Resnet50	Open Source (Not specified)	organic wastes and recyclable wastes, recyclable organic, residual, hazardous	resnet	Improved from 88.50–93.50%	[10]
6	Resnet-50(Depth wise Separable Convolution Attention Module - DSCAM)	BR-124(Huawei, Baidu's garbage dataset, Baidu recyclable garbage dataset)	40 classes - Huawei 214 classes- Baidu 21 classes – Baidu Recyclable	resnet	91.20%	[11]
7	Efficientnet	huawei	harmful garbage and kitchen garbage, recyclables and other garbage	Efficientnet	After 30 epoch training, the average accuracy reached 93.47%, and the highest was 98.3%	[15]

Sr. No.	Name of algorithms	Dataset	classes	Algorithm Outperformed	Acc. Of algorithm outperformed	Reference
8	Gnet (ResNeXt 32×16d and ResNeXt 32×8d)	Huawei	43 categories	Gnet (ResNeXt 32×16d and ResNeXt 32×8d)	accuracy of 96.96%	[16]
9	InceptionV3 networks	Kaggle dataset	12 classes of waste images, battery, biological, brown-glass, cardboard, clothes, green-glass, metal, paper, plastic, shoes, trash, and white glass	InceptionV3	93.1% accuracy on the test dataset 95.85% accuracy on train dataset	[17]
10	improved algorithm based on ResNet-50	not specified (2527 images same classes)	glass, paper, plastic, metal, cardboard, and trash.	improved algorithm based on ResNet-50	After giving 20 epochs we got nearly, 95% accuracy.	[18]
11	AlexNet, ResNet, VGG16, and InceptionNet	trashnet, waste classification data, Drinking waste classification	(glass, paper, cardboard, plastic, metal, and others) – trashnet (organic and recyclable objects)- waste classification data (glass, aluminum cans, PET, and HDPE)- drinking waste classification	Alexnet and resnet	AlexNet : trac-98.27%, val-acc-97.95% ResNet : trac-97.94%, val-acc-97.21% InceptionNet V3 : trac-98.15%, val-acc-96.23% VGG16 : trac-98.76%, val-acc-87.52%	[19]

Sr. No.	Name of algorithms	Dataset	classes	Algorithm Outperformed	Acc. Of algorithm outperformed	Reference
12	ResNet50, DenseNet169, VGG16, and AlexNet	Imagenet dataset (2527 images same classes + 1636 new images added)	glass, metal, paper, plastic, trash	Resnet50, Densenet	AlexNet – 89.3 VGG16–91.7 ResNet50–93.4 DesneNet169–94.9	[20]
13	ResNet50	images taken by a camera.	recyclable garbage, non-recyclable garbage, kitchen waste and other garbage	Resnet50	test acc 94.85%	[21]
14	EfficientNetB7, Inception V3, NaSNet-Large, ResNet50, ResNet50-V2	Kaggle (2527 images)	cardboard, glass, metal, paper, plastic, and garbage	Resnet, inception.	best results are obtained in ResNet50-V2(97.07%) and InceptionV3(0.9469), and the worst results are obtained in EfficientNetB7(0.2445)	[23]
15	Faster RCNN with Inception -v2 Faster RCNN with ResNet-101 RFCN SSD	a new dataset created (google images, real world images, trashnet dataset images)	10 classes of litter/waste objects	Faster RCNN with Inception -v2 Faster RCNN with ResNet-101	92% mAP 83% mAP	[24]

The models were trained and tested on Kaggle dataset. We tried to test the algorithms that were resulted to be good by other researchers. We considered mobilenet [10] that got accuracy of 93.35% (15% test size) using a quite similar Kaggle dataset of size around 2400 images. For our research we evaluated mobilenet model using Kaggle dataset of size 2527. We got outstanding accuracy for training dataset (60% size) and 95.17% (40% size) for testing set. Next algorithm which we considered was resnet50. Lot of researchers have used the resnet50.

7. Conclusion

We have tested the best algorithms by the other researchers, and we can conclude that the performance of the algorithm is data driven and depends on fine tuning. The more the amount of data is given to the algorithm, the better will it perform. We choose the algorithms for our experiment that gave best results to other researchers. We built our models on Kaggle dataset. The dataset contained 6 classes of garbage that were cardboard, metal, paper, plastic, glass and trash. Then we compared and reviewed theses algorithms on basis of their accuracy. MobileNet outperforms in case of training accuracy. Resnet and Inception gave testing accuracy above 90%.

8. Future Scope

We have identified algorithms for our study and experimentation that have already demonstrated superior performance in the experiments conducted by other researchers in the field of garbage classification by considering only accuracy performance metric, not considered other metrics like F1-Score, precision, recall and support. We have thoroughly tested these algorithms and compared their results only for the accuracy metric. However, it is also possible that we may have overlooked other algorithms during our review of similar studies. In the future, we plan to expand our research by considering other remaining performance metrics and reviewing additional studies on garbage classification that may have utilized different algorithms. Furthermore, we aim to advance our study by implementing real-time garbage classification using the algorithms we have investigated.

Declarations

Ethical Approval (applicable for both human and/ or animal studies. Ethical committees, Internal Review Boards and guidelines followed must be named. When applicable, additional headings with statements on consent to participate and consent to publish are also required)

- Availability of supporting data: Not Applicable

- Competing interests: Not Applicable

- Funding: Not Applicable

- Authors' contributions: Sachin Bhoite and Siddhant Buchade collaborated on this research paper and made significant contributions to its conceptualization, design, and execution. The individual roles and contributions of each author are outlined below:

Sachin Bhoite:

Conceptualization: Sachin Bhoite played a crucial role in conceiving the research study, outlining the primary objectives, and formulating the research questions.

Methodology: Sachin Bhoite actively contributed to the design of the systematic review methodology, including the selection of AI techniques, databases, and search strategies.

Data Analysis: Sachin Bhoite participated in the analysis of the collected data, with a specific focus on aspects related to AI applications in diabetes mellitus research.

Writing: Sachin Bhoite contributed to drafting the abstract and manuscript, providing insights into the interpretation of AI's role in the context of diabetes management.

Critical Review: Sachin Bhoite critically reviewed the manuscript, offering valuable feedback and ensuring the accuracy of the presented information.

Siddhant Buchade gar:

Literature Review: Siddhant Buchade extensively reviewed the existing literature on AI applications in diabetes mellitus, contributing to the identification of gaps in knowledge and the current landscape.

Data Collection: Siddhant Buchade actively participated in the collection of relevant studies, ensuring the comprehensiveness of the systematic review.

Data Synthesis: Siddhant Buchade played a key role in synthesizing the findings from diverse studies, facilitating the identification of overarching themes and patterns.

Writing: Siddhant Buchade contributed to the composition of the abstract and manuscript, focusing on communicating the findings of the systematic review in a clear and concise manner.

Critical Review: Siddhant Buchade critically reviewed the manuscript, providing constructive feedback and ensuring the coherence of the content.

Both authors, Sachin Bhoite and Siddhant Buchade, are accountable for the overall integrity and accuracy of the research. Their collaborative efforts have enriched the paper by offering a comprehensive exploration of AI applications in diabetes mellitus research and emphasizing the need for a balanced consideration of both advantages and disadvantages.

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Figures

Figure 1

Sample garbage images (plastic, metal, glass, paper, cardboard, trash)

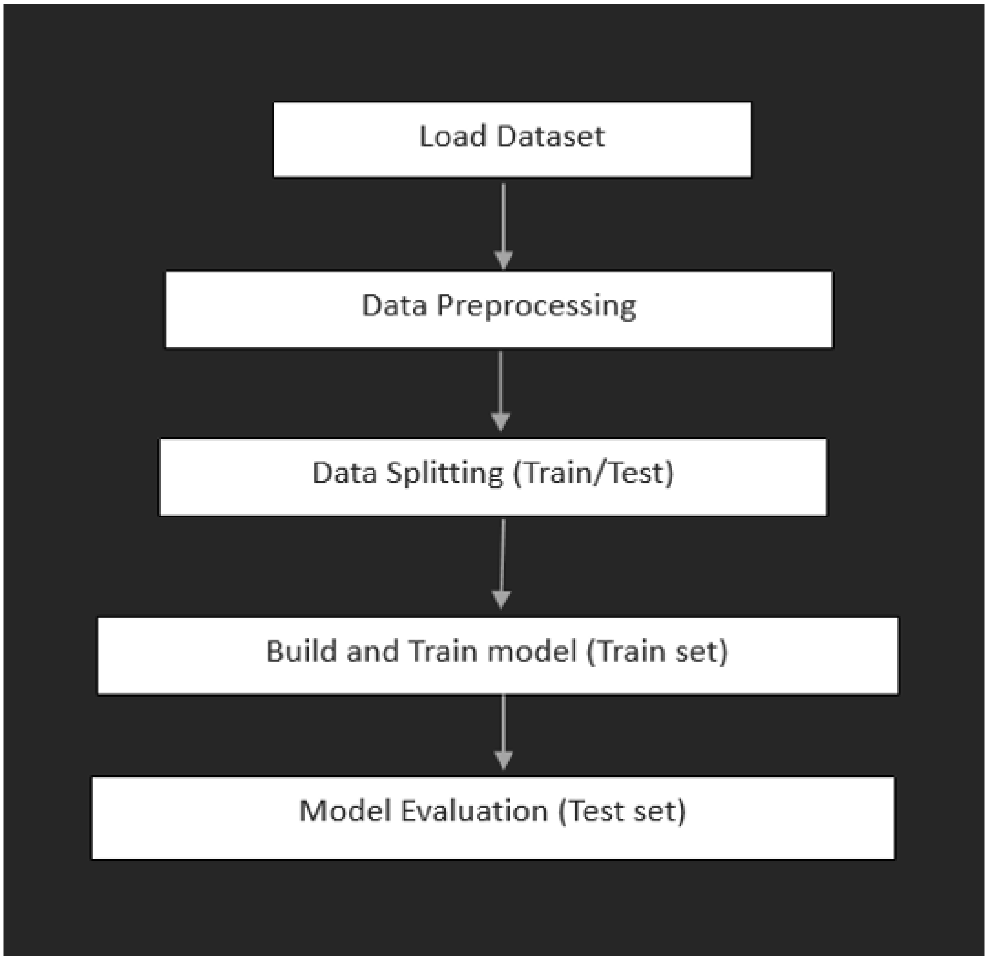

Figure 2

Machine Learning Pipeline used for our study