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Assessing MobileNetV3 for Plastic Waste Segregation

by

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Abstract

To improve effective waste management practices at an individual level, ease of access to information is crucial within the South African context due to the informal manner in which it handles its plastic waste. The informal manner in which South Africa handles its plastic waste is linked to the lack of information that is accessible and reliable for public use (Jansen & Roberts, 2018). By addressing this issue, plastic waste recycling can be facilitated within households by providing individuals with information that is easily accessible. Convolutional Neural Networks (CNNs) can be used as a tool to improve effective individual plastic waste management by improving available information for public use to empower individual rights on plastic waste management practices. This will result in an increase in individual recycling behaviour at an individual level. Waste needs to be classified into different waste types due to the different methods of disposal that are required for each waste type. In terms of plastic waste, it can be recycled and reused as raw materials for production. However, the reprocessing of one type of plastic is not the same as the reprocessing of another type of plastic. A waste classification system is needed to improve access to information that is provided to the public, which is limited to the recycling of plastic waste. Thus, this research project aims to evaluate the suitability of using MobileNetV3 to run a waste classification AI. A model of MobileNetV3-Small was used as the architecture for the neural network because it is the latest architectural framework within the MobileNet family. The model was built and trained on the Keras Tensorflow open-source library and was developed for the Wadaba dataset, which is available at: https://wadaba.pcz.pl/. The MobileNetV3-Small architecture was tested at three different learning rates 0.0001, 0.001, and 0.01 to determine at which learning rate the model performs the best at recognizing the Wadaba dataset. It was found that at a learning rate of 0.0001, the model achieved an accuracy score of 59% with a validation loss of 1.21. At a learning rate of 0.001, the model achieved an accuracy score of 61% with a validation loss of 1.21. At a learning rate of 0.01, the model achieved an accuracy score of 61% with a validation loss of 1.24. The significance of the findings is that the model can recognize the Wadabba dataset with an average accuracy of 60% across the three learning rates, suggesting that the model can be used in applications that involve plastic waste classification.

1. Introduction

A waste stream refers to the flow of specific waste types from their source to recovery, recycling, or disposal (Alabi, et al., 2019). Plastic waste is the world's leading waste stream due to our high dependency on it as a material that is durable, versatile, and affordable (Alabi, et al., 2019). However, plastic waste pollution can have detrimental environmental impacts, affecting our wildlife habitat and human health. This is evident in the globe's rate of generating municipal solid waste, which is approximately 2.01 billion tonnes annually (The World Bank, 2021). On an individual level, the average municipal solid waste generation per person per day ranges between 0.11 kg - 4.54 kg (The World Bank, 2021). Out of the total 2.01 billion tonnes of municipal solid waste, 66 millions of tonnes (33%) of that waste is not managed ecologically (The World Bank, 2021). 5 million tonnes of plastics are used annually by developed countries, with only one-quarter of it being recycled each year (Jansen & Roberts, 2018). This sums up to three-quarters of the plastics being used by developed nations that are not recycled or reused and are disposed of instead. This can result in plastic waste entering our environment, polluting our oceans, and causing significant damage to our ecosystems due to landfill overfill and poor waste management practices. Where there is a need to divert this flow of waste from its source point rather than an endpoint.

Within developing countries, most of their plastic waste enters our environment through unregulated landfill sites (Babayemi et al, 2019). This is attributed to the informal nature of how these countries deal with their plastic waste. As a result, heavy reliance is placed on landfill sites to dispose of their waste because it is a cheap method of disposal, but not a sustainable one. It is predicted that by 2050, global municipal solid waste will increase to about 3.40 billion tonnes (The World Bank, 2021). In addition, it is predicted that high-income countries (developed nations) will see a 19% increase in daily per capita municipal solid waste generation (The World Bank, 2021). Middle-low-income countries (developing nations) will see an increase of 40% in municipal solid waste generation (The World Bank, 2021). This states that our waste generation will increase as a result of our consumption.

The role that consumers and the public play regarding waste management initiatives, such as recycling, is crucial since the consumer plays a vital role in the flow of products and their end-of-life cycle, leading to recycling. However, consumers are often confused about how a product should be recycled, or they do not know which items can be recycled (Sadan & de Kock, 2020). The effectiveness of individual engagement in the management of plastic waste relies on factors such as whether individuals are aware and if they have information about the waste that they are dealing with. Currently, information is being communicated to the public through product labelling, which is known as on-pack recycling labelling (Handfield, 2017).

This includes visual signals such as signs and symbols to inform the consumer as to what they should do with the product once they are done using it. However, on-pack recycling labelling is not standardized within South Africa and varies across different retailers and brands, especially within informal settings (Handfield, 2017). An example is that consumers who reside within informal settlements and rural areas within South Africa do not have easy access to information on plastic waste recycling, adding to the challenge of public recycling within the country for plastic waste (Sadan & de Kock, 2021). This pertains to the question "Are consumers able to correctly identify a product that can be recycled, and do they have access to information about that product, how to separate that product, and what methods of disposal are available?".

Access to information is a right to meaningful individual engagement, and this is associated with a clean environment and an environmental government (Wouters, et al., 2011). Accessible information and civil society engagement are fundamental to environmental management, but this is often hindered by a lack of information (Wouters, et al., 2011). Meaningful individual engagement needs to provide participants with the right information, in a format that is accessible, and at the right time to facilitate meaningful engagement from the public (Wouters, et al., 2011). This lack of meaningful individual engagement, awareness, and involvement of the public for plastic waste has resulted in consumers not being empowered to manage their waste. However, through the use of technology, plastic waste recycling can be improved on an individual level due to accessible information being provided to the public.

Individual engagement in recycling is hindered by several factors that are interrelated such as a lack of knowledge, a lack of environmental awareness, difference in cultural and social attitudes and norms, inconvenience to recycling facilities, perceived ineffectiveness of recycling activity, economic barriers such as a lack of incentives, lack of adequate recycling technology, and a general mistrust within the system overall (Balunde, et al., 2020). Each factor contributes to the lack of individual recycling activity, however, each factor impacts an individual differently. For example, the lack of knowledge and environmental awareness is attributed to the ease and frequency of access to information for recycling initiatives. A deterrent to this factor is the result of misunderstandings and the lack of knowledge about recycling, and as a result, individuals are practicing poor recycling habits. In terms of attitudinal differences and perceived ineffectiveness, group attitudes differ amongst the individuals within the group. Individual attitude is influenced by intrinsic factors such as individual general knowledge and individual experiences, or extrinsic factors such as environmental or social influence. In practice, attitudinal differences impact public participation and the engagement of communities in recycling initiatives and sustainability initiatives. The economic costs that are associated with recycling contribute to the level of individual engagement in recycling initiatives. Low-income houses are impacted the most due to the costs associated with collection services for plastic waste, and the need to purchase special waste bags and bins (OECD, 2008). As a result, economic barriers around recycling act as a deterrent, specifically for low-income households who find it cheaper not to recycle at all. Incentives would then have to be provided to combat this deterrence. In order to tackle these factors, the role of technology can be used as a tool to improve recycling initiatives on an individual level.

1.1 Technology as a tool to improve waste segregation

Technology can be used to mitigate the factors that hinder individual engagement in recycling. In terms of knowledge and environmental awareness, technology can be used to bridge the gap in information that can be provided to individuals on how to recycle waste (Thiagarajan, 2020). In addition, this bridge in the gap of information also relates to the ease of access that individuals will have to information on how to dispose of waste. Individuals will be influenced by the information that is available to them, which will allow individuals to make informed decisions on how to properly dispose of and recycle waste (Shah & Kamat, 2022). In terms of cost effectiveness, technology can be used at different tiers, where specialized tasks can be performed on devices that do not require extensive hardware or software specifications. This allows for a user-friendly device that can be accessible to the public (Thiagarajan, 2020). Various models of computer vision are tasked with waste identification and classification, with this study focusing on the use of MobileNet to provide ease of access to information for the public on plastic waste.

1.2 MobileNet as a strategy for plastic waste segregation

MobileNets are a family of mobile-first computer vision models, made for Tensorflow, which are a class of Convolutional Neural Networks (CNNs) that were designed by Google researchers, that are resource-friendly and can run immediately on mobile phones (Rabano, et al., 2018). It is designed for efficient accuracy maximization, where it considers the restrictions of resources for an embedded application (Rabano, et al., 2018). MobileNets are a lightweight neural network model that has low-latency and low-power models that are structured to meet the resource limitations of devices such as mobile phones (Glegola, et al., 2021). Latency refers to the time delay between the network's input and its output (Li, et al., 2021). Having a reduced latency means less time delay between the network's input and its output, where the device can return a classification of an image at a faster rate. This is crucial for real-time applications, whereby reducing the latency of a CNN improves its performance and responsiveness to CNN-based applications (Li, et al., 2021). MobileNet models are created for classification, detection, embeddings, and/or segmentation purposes, making this model capable of detecting and classifying plastic waste on a mobile platform (Bobulski & Kubanek, 2021).

Resource-constrained devices such as smartphones differ from Personal Computers (PC), where PCs have processors that are more robust than smartphones (Harris & Cooper, 2018). PCs can handle more demanding tasks and applications compared to smartphones, since they have a greater storage capacity and more RAM, making them more effective at multitasking (Cordella *et al., 2021*). PCs can achieve higher performances compared to smartphones, the reason is that advanced cooling systems are present within PCs, which allows them to maintain high performances over long durations (Cordella *et al., 2021*). In contrast to PCs, smartphones are designed to be more portable, and for this reason, efficiency is a key design feature of smartphones (Harris & Cooper, 2018). Smartphones use ARM processors, which are less powerful than the standard processors of PCs but are highly efficient (Cordella *et al., 2021*). An example is that modern-day smartphones are capable of high-end use, such as high-definition recording, locating objects, estimating distance, producing digital documentation, multilingual communication, location guidance (GPS), interpreting code, streaming audio, as well as predicting climate (Harris & Cooper, 2018).

1.3 What is MobileNetV3

The MobileNetV3 architecture is a CNN that is designed to be lightweight and optimized for the Central Processing Unit (CPU) of mobile devices (Howard, et al., 2019). MobileNetV3 is twice as fast at developing image classifications compared to the previous models of MobileNetV2 and MobileNetV1 on mobile CPUs (Glegola, et al., 2021). The architecture of MobileNetV3 is highly customizable, whereby it offers different configurations for developing image classifications (Howard, et al., 2019). MobileNetV3 is designed to be similar in structure to MobileNetV2, where the two versions share common building blocks (Howard, et al., 2019). There are two models for MobileNetV3 known as MobileNetV3Large and MobileNetV3Small. For this project, MobileNetV3Small has been picked as the desired model. MobileNetV3Small is 4.6% more accurate compared to MobileNetV2, with a reduced latency of 5% (Howard, et al., 2019). MobileNetV3Large is 3.2% more accurate on ImageNet classifications in comparison to MobileNetV2, with a reduced latency of 15% (Howard, et al., 2019). Thus, for ImageNet classification, MobileNetV3Large is deemed more suitable, however, this project makes use of the Wadaba dataset, which is more suitable for MobileNetV3Small since it is more accurate overall and has reduced latency.

1.4 Problem Statement

The problem to be addressed through this project is the ease of accessibility to information for the public, which is limited to the recycling of plastic waste. Within South Africa, the informal manner in which it handles its plastic waste is linked to this lack of accessibility to information that is convenient and reliable for the public (Jansen & Roberts, 2018). Artificial intelligence (AI), such as CNNs, can be used as a tool to mitigate the limited ease of access to information for the public's needs by providing on-demand information on best recycling practices based solely on an image of the waste in question. Specifically, the use of MobileNetV3 can be used as a tool for public access to information about plastic waste recycling due to its capabilities to be implemented on mobile devices, which are ubiquitous and do not have advanced hardware specifications (Habib & Qureshi, 2022). This is attributed to the model's structure, which does not require a high computational load to perform on mobile CPUs (Alzubaidi, et al., 2021).

By researching this issue, plastic waste recycling within households can be facilitated. This is done by providing the individual with information that is easily accessible. It would assist the plastic waste management situation within South Africa, where this system can be used to promote individual engagement by giving individuals information on how to treat or dispose of their plastic waste. The system will result in knowledge and awareness for the general public. It is a new software system where the system can help tackle the problem of the disposable mentality amongst South African individuals. Individuals can be empowered to manage their plastic waste by gathering information on it and being able to identify it. If individuals have access to information, this can promote individual engagement in plastic waste recycling. Whereby Individuals can make informed decisions about how to deal with their plastic waste. As a result, individual recycling power will increase, and residents can make an informed decision on how to treat their plastic waste or how to dispose of it ecologically.

However, the suitability of MobileNetV3 to classify plastic waste needs to be established before such a system can be widely implemented. Therefore, this research aims to fill that gap by assessing whether MobileNetV3 can classify plastic waste from a single image and which parameters are needed to optimise its performance.

1.5 Motivation

For effective waste management to be achieved at an individual level, the use of CNNs can be used as a tool to increase individual recycling behaviour and improve information availability to the public to empower their rights in waste management practices. Previous research that has been done within the field of CNNs has been progressing over the last decade. This has resulted in significant advancements made within a variety of computer vision tasks such as image classification (Glegola, et al., 2021). There is a trend within the design of CNNs to find more powerful models that can achieve super-human accuracy.

However, the cost of high accuracy comes at the expense of increased computational time, increased memory usage, and increased energy consumption (Glegola, et al., 2021).

Recent research within the field of CNNs focus on the design of lightweight architectures that have fewer parameters and require less computational load while maintaining their accuracy (Bobulski & Kubanek, 2021). New research within the field of CNNs has turned to the advancements of systems-on-a-chip, where the increased demand to run high-quality CNNs on resource-constrained devices, such as mobile devices, is made possible. Architectures such as MobileNetV3 are examples of such a CNN that can operate on mobile devices for individual use.

1.5.1 How information makes a difference

Information can help us to quantify and structure problems at hand, where for individuals, the use of information at their disposal provides a meaningful insight into the problem at hand and how to make informed decisions to solve these problems (Khedia, 2016). This process is summarised into the three general steps being 1) identify needs, 2) identify the problem, and 3) build custom solutions (Khedia, 2016). To ensure the proper treatment of waste, waste needs to be properly classified into different types of waste, which requires different methods of disposal (Khedia, 2016). Regarding plastic waste, certain plastics can be recycled and reused again as raw materials for production, however, the reprocessing for one type of plastic is different from another (Khedia, 2016). The question at hand is to provide individuals with information that is easily accessible through the use of CNNs such as MobileNetV3 to better inform their decision-making on plastic waste recycling.

Therefore, this dissertation aims to train and assess a deep-learning CNN system that utilizes the MobileNetV3 architecture for plastic waste classification. This will increase individual participation in plastic waste management. Where individuals can be informed about what type of plastic waste they are dealing with, how to dispose of it, or how to recycle that waste. Individual empowerment towards waste management will increase due to more information being made easily accessible, thus increasing public involvement and awareness in plastic waste recycling.

1.6 Aims & Objectives

1.6.1 Aim

The ability of CNNs to classify waste has already been demonstrated. However, the ability of a CNN to classify waste on a resource-constrained architecture such as a smartphone needs to be established for its benefits to be realized. Therefore, this study aims to determine whether a CNN specifically designed for a smartphone (such as MobileNetV3-Small) can reach an acceptable level of accuracy on a waste classification task.

MobileNetV3 offers new and efficient versions for nonlinearities that are more suitable for mobile devices and settings (Glegola, et al., 2021). Whereby efficiency is maintained, and the new and improved versions of nonlinearity can be used to improve performance (Howard, et al., 2019). Thus, MobileNetV3 offers a solution for real-time applications such as image recognition and classification, as well as edge object detection without using extensive computational resources (Howard, et al., 2017).

1.6.2 Objectives

- Objective 1- To develop a MobileNetV3-Small Model for the application of plastic waste classification and segregation on mobile devices
- Objective 2- To train the model on the Wadaba dataset of plastic waste images
- Objective 3- Evaluate the model's performance

The research problem that is investigated is focused on whether MobileNetV3 is capable of classifying and segregating plastic waste.

2. Literature review

2.1 Plastic waste is a major issue.

Plastics are made up of synthetic organic polymers, and have a wide range of applications and uses such as water bottles, food packaging, electronic goods, construction materials, and clothing (Alabi, *et al*., 2019). Initially, it was thought that plastic was harmless and inert and within the last six decades, plastics have become indispensable and versatile with different chemical compositions and applications (Alabi, *et al*., 2019). However, the accumulation of plastic in the environment over many years has had adverse impacts. Environmental pollution caused by plastic is now a major environmental concern in both aquatic and terrestrial environments (DFFE, 2020). Plastic waste is one of the world’s leading waste streams due to our dependency on it and additionally, options for plastic removal are limited (Sadan & de Kock, 2020).

The problem with plastic disposal and treatment is that currently, when plastic items reach their end-of-life cycle, most plastic material escapes onto land and into various water sources such as rivers and oceans (DFFE, 2020). In addition, most plastic materials also take a significant time to degrade and disappear, ranging between 20 – 500 years (DFFE, 2020).

Within South Africa, plastic is the most problematic waste stream, whereby it occupies the majority of landfill sites, illegal dumping sites, and water sources (DFFE, 2020). According to a study conducted by the DFFE (2021) on plastic material flow confirms that plastic packaging makes up the largest component of single-use packaging products within South Africa. The generation of single-use plastics for packaging is expected to increase even further due to population growth and urban expansion (DFFE, 2021). The growing middle class of South Africa further stimulates this by creating a large consumer market for plastic goods (Jansen & Roberts, 2018). In addition, the informal economy of South Africa has also increased the use of non-compliant plastic carrier bags, which find their way into the waste stream (Sadan & de Kock, 2021). Many informal settlements within South Africa are situated along the main rivers of the country such as Hennops, Jukskei, Palmiet, and Umgeni (Sadan & de Kock, 2021). This allows for single-use plastic waste to enter these river systems due to poor waste management infrastructure, the lack of public participation and awareness, and the use of illegal dumping sites within these areas (Sadan & de Kock, 2021).

We have a disposable mentality when it comes to the management of plastic waste (O'Brien, 2013). Disposable mentality refers to the current phenomenon where many items are designed to be disposable, where they are designed for single use or only for limited use and then thrown away (O'Brien, 2013). In addition to this, the rate at which plastic deteriorates creates a situation of plastic waste overflow (O'Brien, 2013). Where landfill sites are overflowing with plastic waste, resulting in an issue of space for other waste types (O'Brien, 2013). This problem is attributed to the lack of plastic recycling within South Africa due to its lack of public participation in waste management (Sadan & de Kock, 2020). The average recycled content for plastic within South Africa was 17% in 2018, which indicated that only 17% of plastic material is flowing back into the economy (Sadan & de Kock, 2020). However, more than 40% of plastics in South Africa are not recycled each year (Sadan & de Kock, 2020). The reason for this is that although recycling is a key element for the circulation of plastic material within the economy, not all plastics are currently recycled in practice in South Africa (Sadan & de Kock, 2020).

2.1.1 Different types of plastic that impact the environment

There are different types of plastics based on their constituents and the type of material used in their production (Alabi, *et al*., 2019). Table 1 in Appendix 1 represents the different types of plastics, their common uses, their properties, and what they are recycled into. One element that is not included in Table 1 is the size of plastics (Alabi, *et al*., 2019). There are two major classifications of plastics: 1) macroplastics, which are plastics that have a diameter greater than 20mm, and 2) microplastics, which are plastics that have a diameter less than

5mm (Alabi, *et al*., 2019). No classification for plastics has a diameter between 5-20mm. Macro plastics include general household plastic items such as detergent bottles, milk bottles, plastic containers, plastic cutlery, packaging tape, and refuse bags (Alabi, *et al*., 2019). For the interest of this research, macroplastics make up the entirety of the Wadaba dataset, which was used to train the MobileNetV3 model, and microplastics are not considered.

2.1.2 Recycling rates of developed and developing countries

Within the past 20 years, global plastic waste recycling has increased, and OECD countries like the European Union, India, and China have contributed towards this growth (Samborska, 2024). In 2018, the European Union had seven EU member states that recycled more than half of their generated plastic waste at an estimated 41.5% (European Union, 2021). Out of the seven EU member states, the highest rate of plastic recycling was reported in Lithuania at 69.3%, in Slovenia plastic recycling at 60.4%, in Bulgaria at 59.2%, Czechia at 57%, Cyprus at 54.3%, Slovakia at 51.4%, and Spain 50.7% (European Union, 2021). However, less than a third of plastic waste was recycled in other European countries such as Malta with a rate of 19.2%, France has a plastic recycling rate of 26.9%, Luxembourg has a recycling rate of 32.3%, Austria has a recycling rate of 31.9%, Denmark at 31.5%, Finland at 31.1%, Ireland at 31%, and Hungary at 30% (European Union, 2021).

In 2019, global plastic recycling rates were 12-13%, with non-OECD Asian countries and Latin American countries also contributing to this rate, but at a slow rate (Samborska, 2024). According to OECD data, countries such as the United States of America, the Middle East, and North Africa have seen advances in plastic waste recycling, but these advancements are not rapid, with the United States of America achieving a recycling rate of 4.5% (Samborska, 2024).

Within the African Union, there is available data on 33 African countries for the Import of plastic products from 1990 to 2017 (Babayemi et al, 2019). During this period, Africa as a whole has imported 203Mt of plastic products valued at $285 billion (Babayemi et al, 2019). From this, the largest share of plastic imports comes from Egypt with a share of 43Mt (18%), Nigeria with a share of 39Mt (17%), South Africa with a share of 27Mt (11.7%), Algeria with a share of 26Mt (11.3%), Morocco with a share of 22Mt (9.6%), and Tunisia with a share of 16Mt (7%) (Babayemi et al., 2019). From 2009-2015, primary plastic production within eight African countries contributed to 15 Mt (Babayemi et al., 2019). This shows that plastic import and plastic production are commonly practiced within Africa, with the top-performing African countries in economic growth contributing the most. However, environmentally sound end-to-end management of plastic waste through recycling and recovery is only within its infant stage in Africa, whereby recycling initiatives have already started in a few African countries (Babayemi et al., 2019).

The recycling sector within Egypt is making strides, with about 1.5 million tons of plastic being recycled in 2022/2023 (Hashem, 2020). Egypt ranks 1st on the African continent for recycling rates (Hashem, 2020). Currently, 28 recycling facilities are operational in Egypt, with a plan to increase to 56 recycling facilities (Hashem, 2020). For Nigeria, only 2% of its plastic is being recycled, where initiatives are placed on other sectors within the country that need more support than their waste management initiatives (Chinedu, *et al.*, 2018). Within South Africa, only 10% of the country's plastic is recycled, leaving the other 90% dumped in landfill sites (Statistics South Africa, 2018). Informal recycling within South Africa plays a major role in its waste management initiatives, with informal reclaimers being responsible for 51% of South Africa's waste being recycled (Statistics South Africa, 2018). Algeria recycles 30% of its annual plastic production of 13 million tonnes, which is equivalent to 3.9 million tonnes of plastic, with the Algerian government planning to increase this percentage (Hachemi, *et al.*, 2024). For Morocco, it is difficult to establish a formal recycling system within the country due to Morocco's current waste management situation (Taouahria, 2024). Only 8% of Morocco's waste is being recycled within the country (Taouahria, 2024). Within Tunisia, its recycling sector is almost entirely driven by the informal waste sector (Jamel, 2018). Where only 4-7% of Tunisia's waste is recycled (Jamel, 2018).

2.2 Meaningful individual engagement is an important driver of recycling.

Individual engagement is a crucial driver for recycling initiatives because the individual has a massive influence on the value chain of recycling (Ertz, et al., 2023). The individual, who is deemed as the consumer, plays a vital role in the life cycle of a product from its use to its disposal and recovery (Ertz et. al, 2023). There are several key areas where public participation regarding recycling plays a major role in environmental management such as increased rates of recycling, improved quality of recyclables, improved economic benefits, reduced environmental impact, improved resource conservation, increased community awareness and community education, as well as policy support (Barrutia, et al., 2015).

The rate of recycling can be increased through effective individual engagement, whereby if the individual can effectively manage and sort their plastic waste from other municipal waste, more plastic waste is diverted from landfill sites and directed to recycling facilities, resulting in a more efficient recycling process (Kubanza & Simatele, 2019). The quality of recyclables is improved through the efficient sorting of waste by the public, which reduces mixed waste streams that often end up in landfill sites and allows for plastics to be processed more easily (Kubanza & Simatele, 2019). Improving individual engagement for recycling can lead to economic benefits, whereby efficient individual engagement can lower the costs that are associated with plastic waste management (Xu, et al., 2018). The public can also help to support the recycling industry, where it can stimulate job creation and promote community growth and sustainability through engagement initiatives (Xu, et al., 2018). Overall environmental impact is reduced through efficient individual engagement, where meaningful individual engagement reduces the amount of plastic waste generation and diverts plastic waste away from various disposal points such as landfill sites, waterways, and oceans. In addition, active individual engagement in plastic recycling helps to reduce the global carbon footprint that is associated with the generation and production of new plastics (Barrutia, et al., 2015). Thus, the individual can help to reduce the rate of resource consumption through the conservation of resources instead. Where natural resources such as petroleum, which is used to generate and produce new plastics, are reduced due to the public reusing and recycling their plastics instead of disposing of them (Barrutia, et al., 2015). As a result, increasing the knowledge and awareness of the public further implements a culture of responsibility for the environment. Meaningful individual engagement and education on recycling and how to dispose of plastic waste correctly will encourage sustainable waste management practices and raise awareness about environmental impacts and issues (Steg & Vlek, 2009).

2.2.1 Factors that hinder individual engagement

Several barriers can hinder individual engagement in recycling, such as a lack of knowledge and environmental awareness; cultural and social norms and attitudes; inconvenience; The lack of adequate technology and infrastructure; perceived ineffectiveness; economic barriers; lack of incentives; and a general mistrust within the system. Knowledge is a crucial factor since it forms the foundational understanding of the issue at hand. A lack of knowledge and awareness about plastic recycling will result in individuals being unaware of the importance of plastic recycling and how to properly recycle different plastic types (Balunde, et al., 2020). A deterrent of meaningful individual engagement in plastic recycling is attributed to the misunderstandings and the lack of knowledge about which plastic types can be recycled, and how this waste needs to be prepared for the recycling process (Berthoû, 2013). Consumer behaviour can be changed through education, an example of this is the knowledge of the lifespan of plastic items such as plastic packaging, and how to recycle and dispose of these items (Capiene, et al., 2021). Individuals who are knowledgeable about plastic recycling can ecologically dispose of plastic waste due to their general knowledge of how to dispose of this type of waste (Capiene, et al., 2021). However, the tool of education needs to be complemented by additional incentives and other various measures to improve the quality of education that is being delivered about plastic waste and how to manage this waste stream (Xu, et al., 2018).

Convenience is a factor that is just as important as knowledge in terms of hindering meaningful individual engagement in plastic recycling. It affects all the factors that hinder individual engagement within a waste management initiative, due to the ease and frequency of access to information for that initiative (Steg & Vlek, 2009). It strongly impacts household participation in plastic recycling, where it influences attitudes and habits, which can result in individuals being more inclined to engage in plastic recycling because it is deemed neither time-consuming nor difficult (OECD, 2008). According to Okonta and Mohlalifi (2020), it is observed that within the city of Johannesburg, the most important factor that fosters waste separation behaviour is the accessibility to recycling information, with an average importance of 48.37%. This means that 48.37% of households within Johannesburg consider the accessibility to recycling information as an important factor that inclines them to recycle. Thus, the level of convenience is determined by the ease of access, where if ease of access is difficult to obtain, then individuals will be less inclined to engage in plastic recycling since they perceive the task to be time-consuming and difficult.

Collective and social attitudes refer to the beliefs and preferences of a collective rather than the individual (Ertz, et al., 2022). Group attitudes differ from their constitutive members, however, individual attitudes are formed through a top/down or a bottom-up process (Ertz, et al., 2022). How attitudes are formed through a top/down process is from the idea that our brains process an idea from a big picture process that stems from our previous knowledge before breaking it up into specific information. Thus, the top/down process states that individuals perceive the world around them by utilizing their past experiences, expectations, and emotions (Gatersleben, et al., 2012). In regards to the bottom-up process, it suggests that individual perceptual experience is based on sensory stimuli that have been received by using data that is only available from our senses (Darcie, 2011). This makes an individual's attitude be influenced by intrinsic factors such as individual general knowledge and individual experiences, or extrinsic factors such as environmental or social influence. Thus, even though individuals may have a different attitude compared to the collective, when faced with a situation, they come together as a group to share a collective attitude towards the current situation (Ertz, et al., 2022). Cultural and social attitudes impact public participation, and some communities do not prioritize and engage in recycling or environmental sustainability (Tamar, et al., 2020). In contrast, communities that prioritize and engage in recycling or environmental sustainability impact public participation in a positive manner. This is attributed to that communities can promote residential waste separation through social influence techniques such as distributing information that pertains to delivering a predefined standard of waste separation; and providing examples of those who already engage in waste separation to establish normative conduct and prompt social comparison for the better understanding of social expectations (Xu, et al., 2018).

Social modelling is used as a social tool to prompt social engagement within an initiative by providing community members who have volunteered in recycling campaigns to act as leaders within the community to encourage active engagement within the community by providing communication and demonstration (Xu, et al., 2018). According to Okonta and Mohlalifi (2020), for the residents of Johannesburg, social responsibility is a significant driving force for waste separation amongst residents who are university graduates. For residents who only have matric and lower formal education, it is found that financial incentives and access to recycling facilities are the significant driving forces for waste separation (Okonta & Mohlalifi, 2020). The reason for this is due to the level of perception, where the perception of the quality of services provided by the city of Johannesburg is looked at (Okonta & Mohlalifi, 2020). Where, if perception levels are low, incentives are used as a moderator for the intention to positively increase attitude.

Economic barriers can act as a deterrence towards achieving active public engagement for plastic recycling due to the costs that are associated with plastic recycling (Xu, et al., 2018). These costs generally impact low-income households where there are costs associated with collection services for plastic waste, and the need to purchase special waste bags and bins (OECD, 2008). As a result, these associated costs around plastic recycling become a deterrence, specifically for low-income households, where incentives would then have to be provided to combat this deterrence. According to Xu, et al. (2018), incentives are on an individual basis to act as a feedback tool about individual recycling performance. A variety of incentives can be provided, such as individual rewards, pricing schemes, and deposit-refund schemes, that can encourage domestic waste separation. Individual incentives are more effective than contingent or group incentives since they target areas of self-efficacy toward recycling (Xu, et al., 2018). This means that incentives can enhance the individual's feeling of self-efficacy and can increase the willingness of the individual to engage in recycling practices. However, in the case of Malaysia, incentives were seen as undesirable by the recipients due to two perceptions; 1) current incentives are not attractive enough for the participants to engage in domestic waste separation, or 2) the Malaysian population is not generally attracted by motivational factors such as a reward and incentive scheme to increase the engagement in plastic recycling (Tiew *et al*., 2019).

2.2.2 Increasing meaningful individual engagement

To increase meaningful individual engagement in plastic recycling, recycling behaviour and action are influenced by extrinsic factors more than intrinsic factors (Keramitsoglou &

Tsagarakis, 2013). Within provincial towns distance to recycling facilities does not have a significant impact on recycling activity due to readily available space at home. Thus, a mixed-use recycling approach is deemed appropriate to use within this setting (Keramitsoglou & Tsagarakis, 2013). In addition, individuals who lack prior knowledge and experience with plastic recycling prefer systems that are voluntary and flexible instead of mandatory systems (Keramitsoglou & Tsagarakis, 2013).

Platforms that provide information can be used as a tool to educate individuals on how to recycle plastic waste, as well as the various techniques and systems that are available to the public (Balunde, et al., 2020). Individual outreach is a crucial tool to enact individual engagement to raise awareness within communities about a particular issue and what solutions there are for the issue (Barrutia, et al., 2015). This is done to provide clear instructions as to what rights and powers the public have in managing their environmental affairs, as well as to educate the public on what they can do to mitigate the issue.

Empowering the individual is an important tool to solidify community responsibility, which translates to increased active engagement from the public since they have control over their environmental impacts. Empowering a community can be done through technology and innovation by providing easy access to information for public use. AI can be used as a technological tool to empower individual engagement by providing the individual with a platform that is convenient and not expensive in the form of mobile recycling software. Recycling software can promote and provide individuals with information on the items that they can recycle to further increase their knowledge (Shah & Kamat, 2022). It provides awareness to the individual on what type of waste they are recycling and what recycling practices are the best fit (Shah & Kamat, 2022). Convenience is provided to the individual since information is made available and easily accessible on mobile devices, making it highly accessible for individual use.

In summary, the efficiency of recycling programs depends on the level of individual engagement, economic viability, and environmental benefits. High levels of individual engagement can ensure that recycling programs are implemented successfully and sustainably for long-term use. A public that is more aware and engages in recycling initiatives is likely to support transitions in waste management to combat waste disposal.

2.3 Waste classification using convolutional neural networks

CNNs are a subset of machine learning, where it is a type of Artificial Neural Network (ANN) that at its core involves deep learning algorithms to perform tasks (Bobulski & Kubanek, 2021). CNNs consist of nodes arranged in layers such as an input layer, one or more hidden layers, and an output layer (Khoa, et al., 2020). Each node is known as an artificial neuron, which connects to other nodes and has an associated weight and threshold (Khoa, et al., 2020). A node is only activated if its output is above the specified threshold value, which would result in data being transferred to the next layer of the network (Abubakar, *et al*., 2020). If the output value of any node is below the specified threshold value, the node is not activated, and thus no data is transferred to the next layer of the network (Abubakar, *et al*., 2020).

Generally, the structure of a CNN consists of three layers known as a convolutional layer, a pooling layer, and a fully connected layer (Shah, & Kamat, 2022). The convolutional and pooling layers are stacked one after the other, where the fully connected layer generates the probabilities of class membership (Khoa, et al., 2020). The purpose of the convolutional layer is so that convolutional filters can be applied to the input image of the model to detect features such as shape, edges, and textures (O'Shea & Nash, 2015). The pooling layer will then be used to reduce the spatial dimensions of feature maps, such as the width and height of the object, while maintaining the model's depth (Howard, et al., 2019). This will assist the model in reducing the number of computations needed within the network by reducing the number of parameters within the model. This will make the model more efficient and less prone to overfitting/underfitting.

Overfitting in CNNs occurs when the model is learning the training dataset at a rate that is quicker than expected. It captures the noise and details of the images but performs poorly on data that is new and unseen by the model (Pavlitskaya, et al., 2022). This is generally caused by a dataset that is not extensive enough, and the model struggles to generalize patterns due to a lack of sufficient training. To avoid overfitting, enhancing the model's generalization capabilities through techniques such as data augmentation, regularisation techniques, and batch normalization can be used as a strategy (dos Santos & Papa, 2022). In contrast, underfitting in CNNs occurs when the model fails to accurately model the training dataset. It results in the model experiencing high training loss and large errors (Gavrilov, et al., 2018). To avoid underfitting, complexities can be added to the model, such as more hidden layers, to improve the modelling capabilities of the neural network (Gavrilov, et al., 2018). In addition, to avoid overfitting, datasets need to be diverse and large so that the model can learn more patterns and be able to generalize well from the dataset due to it being trained more to recognize generalizable patterns (Majchrowska, *et al.*, 2022).

CNNs are a predictive modelling technique, and just like other modelling techniques it involves the minimization of a cost function through an iterative process (Bobulski & Kubanek, 2021). CNNs are more robust in architectural design compared to other models, where they can handle both regression and classification problems (Bobulski & Kubanek, 2021). The mathematical model of a CNN is known as a convolution, where the structure of neurons similarly represents the structure of the mammalian visual cortex (Abubakar, *et al*., 2020). The shape of an object is determined by pixel arrangement, where a CNN first recognizes smaller patterns within an image, and then merges them into a more complicated shape (Abubakar, *et al*., 2020). CNNs are an effective solution to the problem of waste classification and sorting at an individual level because they are very effective at recognizing objects within an image (Shah, & Kamat, 2022).

2.3.1 The use of deep machine learning and artificial neural networks

The "deep" within deep machine learning refers to the depth of layers within the neural network, where generally it is a network that consists of more than three layers including input and output (Bobulski & Kubanek, 2021). Such a a neural network is known as a deep neural network. Deep learning differs from machine learning in that deep learning automates the feature extraction process of a section. It eliminates some of the manual human intervention required to be able to use large datasets due to its automated function (Khoa, et al., 2020). By using deep learning, solutions can be reached in the classification of, supervision of, planning for, and treatment of plastic waste on an individual level by using real-time data monitoring, respectively.

Deep machine learning makes use of a dataset to inform its algorithm in two ways: using supervised learning and unsupervised learning techniques. Supervised learning is a subcategory of machine learning and AI that involves the process of using a labelled dataset to train its algorithm to classify and predict outcomes more accurately (O'Shea & Nash, 2015). In contrast, unsupervised learning is a framework in machine learning that makes use of unlabelled datasets to inform its algorithm to learn exclusive patterns (Alzubaidi, et al., 2021). Deep machine learning can analyze data in its raw form, such as text or images, and it can automatically determine the set of features that distinguishes different categories of data from each other (Bobulski & Kubanek, 2021). It does not require human intervention to process the data compared to conventional machine learning (Bobulski & Kubanek, 2021). This allows us to scale machine learning in interesting ways. Primarily, the use of deep learning and neural networks is credited with the increased progress in computer vision, natural language processing, and speech recognition (Khan, et al., 2023).

Currently, it is more efficient to manage waste using today's technology if it is applied properly with the correct settings (Khoa, et al., 2020). The issues of waste image classification can be tackled by the use of deep learning algorithms with high accuracy (Khoa, et al., 2020). Various models for waste image classification exist, such as MobileNet, and other waste net models such as VGG, AlexNet, ResNet, DenseNet, and SqueezeNet (Shah & Kamat, 2022). The majority of learning models for waste image classification achieve high accuracy rates of over 90%, where the difference lies in what they are used for and how they are used (Shah & Kamat, 2022). For example, various models can be developed to specialize in the various areas of waste management practices, such as collection, sorting, recycling, and monitoring of plastic waste. For this project, the MobileNetV3 architecture that is used will be developed for recycling.

The architecture of MobileNet makes use of a residual structure that is inverted, where the inputs and outputs consist of thin layers within the residual block, and are bottlenecked. This is in contrast to traditional residual models, which use representations that are expanded for their inputs (Sandler, et al., 2018). The MobileNet architecture makes use of depthwise convolutions that are lightweight to filter features within its intermediate expansion layer, where additionally it is crucial to remove non-linearities within its narrow layers to maintain its representational power (Glegola, et al., 2021). This approach allows for the transformation to be expressive, where it provides a framework that is convenient for further analysis (Dong, et al., 2020). MobileNet's performance is measured by comparing it to other architectures, such as ImageNet classification, for example, where MobileNet's trade-offs between accuracy and the number of operations that are required are measured by multiply-adds, as well as its number of parameters (Dong, et al., 2020).

2.3.2 Review of plastic waste identification and separation methods that utilize CNNs

CNNs used for plastic waste identification have been compared to identify which models operate efficiently at recognizing plastic waste on mobile platforms. According to Chazhoor et al. (2022), the ResNet architecture, which is a variation of ResNet that uses the repeating layer strategy of the ResNet 50-50 architecture, achieved a maximum accuracy performance of 87.44% on the Wadaba dataset for plastic waste recognition. However, once the dataset was implemented on a smaller network, MobileNetV2, SqueezeNet, and DenseNet offered equivalent accuracy to that of ResNet (Chazhoor et al., 2022). In terms of training, AlexNet trains the model in the shortest period but with the lowest accuracy, whereas DenseNet takes the longest to train the model (Chazhoor et al., 2022). In terms of classification accuracy, ResNet is deemed the top model for classifying PE-HD at 97.6% accuracy, whereas MobileNetV2 is deemed reliable for classifying PS with more accuracy (Chazhoor et al., 2022).

When comparing all the models, the ResNet architecture has the highest accuracy for recognizing the Wadaba dataset, with the MobileNetV2 architecture being 0.1% less accurate. However, the MobileNetV2 architecture trains faster in comparison to the ResNet architecture, and when data is large, this difference in training time will increase the use and desirability of MobileNet over ResNet.

The advances in systems-on-a-chip technology have led to an increased demand for the development of intelligent vision systems that can function on low-cost mobile devices (Glegola, et al., 2021). To solve the challenges associated with this demand, focus has been placed on reducing model size and computational complexities (Glegola, et al., 2021). MobileNetV3 is a convolutional neural network that is lightweight and was developed to achieve good trade-offs between latency and accuracy within a single core of a Google Pixel 1 smartphone (Glegola, et al., 2021). However, MobileNetV3 is not fully optimized for platforms that have different hardware specifications, whereas its predecessors may perform better for a specific target platform (Glegola, et al., 2021).

According to research done by Bobulski and Kubanek (2021), a 15-layer MobileNet network that uses images of size 120x120 pixels will achieve better performances compared to a 23-layer MobileNet network that uses images of size 227x227 pixels. A 15-layer network will have a shorter learning time compared to a 23-layer network and will have better performance due to the 15-layer network's ability to generalize properties better due to its network structure having fewer complexities (Bobulski & Kubanek, 2021). The CNN developed by Bobulski and Kubanek achieved an accuracy score of 74% compared to CNNs such as AlexNet, which has an accuracy score of 72%, MobileNetV1, which has an accuracy score of 80%, and MobileNetV2, which has an accuracy score of 86% (Bobulski & Kubanek, 2021). Both MobileNetV1 and MobileNetV2, along with the CNN that Bobulski and Kubanek developed, have less than 10 parameters compared to the 222 parameters of the AlexNet CNN (Bobulski & Kubanek, 2021). This translates to that a 15-layer network will use fewer features for recognition compared to a 23-layer network. Smaller-sized images can be used, which have more useful features and less image noise compared to larger-sized images (Bobulski & Kubanek, 2021). In terms of mobile device use, having fewer parameters allows for the ease of implementation on platforms that have hardware restrictions (Glegola, et al., 2021). Making such a CNN more ideal for use on mobile devices.

For the detection of plastic bottles, research done by Thiagarajan (2020) shows that their CNN achieved an accuracy score of 93.4% for the classification of plastic bottle datasets. The dataset used within their experiment contains 16,200 images, making its exposure to images for the training and validation process four times larger in comparison to the model of this research. Overexposure allows for further training and validation to make the model accurate overall. This is a result of having a large dataset because the model can be able to distinguish more features and be able to generalize well due to the diversity within the dataset (Thiagarajan, 2020). A testament to the accuracy of neural networks for hazardous waste detection was also conducted by Uganya *et al.*, (2022), where their system achieved an accuracy score of 92.15% within 0.2 milliseconds. This indicated that their system is performing well in terms of effectively collecting and predicting waste, highlighting the efficiency of AI-based waste management over traditional waste management techniques. Their research made use of the Internet of Things (IOT), which allows the model to have access to the internet (Uganya *et al.*, 2022). This access allows for the model to connect to other models to exchange data and information. As a result, their network can learn from other systems and devices, increasing the network's ability to generalize well (Uganya *et al.*, 2022). As such, the use of artificial neural networks has the potential to be applied further within the stream of waste management.

Within Ghana, the use of CNNs for the detection and proper treatment of waste is already in research and has been carried out (Abubakar, *et al*., 2020). In addition, various prototypes have also been designed with various algorithms for the segregation process of waste to be even more efficient (Abubakar, *et al*., 2020). This came as a result of improving the shortcomings of previous models. Methods of importing data have also been improved to consider the size and shape of objects for their recognition and classification (Abubakar, *et al*., 2020). According to the research done by Abubakar, *et al*., (2020), their model achieved an accuracy score of 98% for waste classification and separation. The system was developed using SmartPLS software for statistical analysis. The SmartPLS software is a graphical user interface that enables the structuring of the equation model within the network by utilizing Partial Least Squares (Abubakar, *et al*., 2020). This method of equation modelling is used for models that are deemed complex in structure.

One drawback of the systems implemented in Ghana is that feeding data into the system to improve its accuracy and efficiency involves a lot of work (Abubakar, *et al*., 2020). Where an efficient method to segregate waste into several material types is needed, that involves the use of the internet as a backend to play the role of a database (Khoa, *et al*., 2020). This would support the CNN dataset in making smart decisions due to it having a wide range of datasets for material types (Khoa, *et al*., 2020). This would also reduce the resources involved during the training process and construct prototypes that do not require a large space compared to already existing reviews (Khoa, *et al*., 2020). This can improve waste segregation, making it more efficient and reliable.

According to research done by Devi, et al., (2018), manual techniques used to sort waste are less efficient, more time-consuming, and not entirely feasible due to large amounts of solid waste being generated. Their study aimed to deploy the use of a smart garbage management system within India, where it proposed the use of an automated waste segregation system that used a CNN algorithm (Devi, et al.,2018). The system made use of a deep learning-based image classification model, which was used to classify materials into biodegradable and non-biodegradable materials (Devi, et al., 2018). The system was based on object recognition in real-time, and it was suitable to handle large amounts of waste classification processes (Devi, et al., 2018). It made use of a Python index package of Spyder to identify and classify waste material through the provided webcam in the design model (Devi, et al., 2018). The system also made use of open-source libraries such as TensorFlow for this process (Devi, et al., 2018). Only a small percentage of errors were recorded in the segregation process of the study, which proved that the system is effective and efficient compared to manual processes for waste segregation (Devi, et al., 2018).

The implementation of machine learning within households becomes a reality with the use of CNNs on mobile devices. By using a deep learning-based methodology for the management of plastic waste through a mobile setting, the recycling of plastic waste can be facilitated within households (Majchrowska et al., 2022).

3. Methodology

3.1 Dataset

The Wadaba database was developed by Bobulski & Piatkowski, (2018), where the goal of developing this database was based on the creation of a plastic waste database that contains images of household plastic waste. This waste can be automatically selected within sorting plants by using methods of computer vision. The Wadaba dataset has been used in previous studies such as Bobulski & Kubanek, (2021), and Chazhoor *et al.*, (2021). The data set contains 4000 images of plastic objects that vary in colour and transparency, which were separated into 20 different sets of 200 images. The dataset used was secondary data that was collected from the Wadaba Institute's database, which is available at: https://wadaba.pcz.pl/.

3.2 Transfer learning

Transfer learning involves the process of taking features from a previous model and applying them to a similar problem. For example, if a model was designed to identify dogs, it can be used to identify other animals such as cats (Chollet, 2020). Transfer learning is used for tasks where there is little data available to train a full-scale model with no previous foundation. In such a scenario, data augmentation is required (Chollet, 2020). The reason to implement transfer learning is to optimize the accuracy of a neural network that requires large amounts of data, where this data needs to be trained on a powerful Graphical Processing Unit (GPU) to obtain results. However, due to the implementation of transfer learning, the learning process of a neural network changes dramatically due to its computational load being reduced (Chazhoor, *et al.*, 2021).

Transfer learning uses frozen layers, where it freezes the initial hidden layer of the model and fine-tunes the final layers of the model (Chazhoor, *et al.*, 2021). The frozen state of the layers indicates that the model will not be trained, as a result, the weights of the layers will remain unchanged. This is to ensure that random-initialised trainable layers and trainable layers with pre-trained features do not mix (Chollet, 2020). If they do mix, the random-initialized trainable layers will cause large gradient updates during the training process, which will destroy any previous pre-trained features within the trainable layers (Chollet, 2020).

Transfer learning is used for tasks when the dataset has little data available for full-scale model training. Pre-trained models that are already trained on large datasets can be used to improve the transfer learning process of another neural network (Chazhoor, *et al.*, 2021). For this study, transfer learning was applied by using already established libraries such as Keras and Tensorflow MobileNet architecture for plastic waste detection. The architecture was updated to allow for the use of the MobileNetV3-small architecture, so that the trainable weights of the model can be updated for application on the actual data. Thus, transfer learning was used in this study because the dataset that is being used is relatively small, with a limited number of images within each class.

This research made use of import functions to import the various functions that are required to build the model within the Keras interface. Once the functions were imported, the dataset directory was established so that the model could pull images from the Wadaba Dataset. The training and validation batches were then established within the network, where the data had to be augmented for training purposes. The MobileNetV3 architecture was then developed, with the pre-trained weights not being updated to allow for transfer learning. The reason is that we are restricted to the MobileNetV3 architecture. Thereafter, the model was trained for 10 epochs, lasting on average 33 seconds. Then, the accuracy and loss of the model were plotted on a graph for comparative purposes. Thus, the training history was saved, and the process was repeated for the other two learning rates to compare at which learning rate the model classifies and generalizes well.

What was not possible to do was update the pre-trained weights of the model since we are only restricted to the MobileNetV3 architecture. This allows for the process of transfer learning within the model. Thus, the model does not make use of other waste net image classification systems such as VGG, AlexNet, ResNet, DenseNet, and SqueezeNet.

The limitations of using transfer learning include the risk of overfitting or underfitting occurring within the neural network model. Overfitting is the result of the model performing extremely well on the training data that it has been given, but does not perform well on the data that the model has never seen before (Pavlitskaya, S., *et al.*, 2022). Overfitting occurs if the model is too complex, and the training data that it has been given is too small and does not contain enough samples to accurately represent all the input data values (Pavlitskaya, S., *et al.*, 2022). Underfitting is the result of the model not being able to capture the relationship between the input variables and the output variables (Chollet, F., 2020). As a result, underfitting leads to high rates of error in both the training dataset and the data that is unseen (Chollet, F., 2020).

For the purpose of this study, the biases include the use of only plastic municipal waste, with the Wadaba Dataset focusing on the general contents of municipal waste, specifically plastic waste. Thus, for this study, other objects with plastic components, such as various children's toys, electronic devices such as smartphones and laptops, electronic cigarettes, and vaping devices, were not used for training purposes.

3.3 Learning rate

The learning rate of a CNN is a crucial parameter for the training process of the model. It influences the model’s accuracy during the training process by determining how quickly the model updates its weights during the training process (Wu, et al., 2019). The learning rate determines the step size that the model will take to update its weights in response to the errors that the model experiences (Wu, et al., 2019). For training speed, establishing the optimal learning rate is crucial for how fast the model will learn. If the learning rate is high, this can speed up the training process and increase the risk of overshooting optimal solutions, which will lead to instability within the model (Alzubaidi, et al., 2021). In contrast, a low learning rate ensures a stable training process, however, the overall training process of the model will be slow.

For model convergence, establishing the optimal learning rate is crucial for the model to converge to a minimum error (Wu, et al., 2019). A high learning rate will result in the model not converging and oscillating (Alzubaidi, et al., 2021). If the learning rate is low, the model may freeze within a local minimum and fail to find solutions to the given problem (Alzubaidi, et al., 2021).

For fine-tuning purposes, a low learning rate would be used within the beginning stage of the model. The learning rate will be gradually increased to fine-tune the model’s training speed and convergence for effective solutions to its given problem.

3.4 Developing MobileNetV3 on Keras Tensorflow

The images are used within a MobileNetV3 architecture that was developed using the Keras Tensorflow open-source software library. Keras Tensorflow is a high-level open-source software library for deep learning that utilizes the Python interface for CNNs (Keras, 2023).

The open-source library platform was developed by Google, and it supports multiple neural network computations such as TensorFlow, CNTK, and Theano (Keras, 2023). It is user-friendly in design, it is scalable for faster neural network computations, and it is extensible (Keras, 2023). The architecture of MobileNetV3 is highly customizable, and it offers different configurations for the development of image classifications (Howard, *et al*., 2017). MobileNetV3 is designed to be similar in structure to MobileNetV2, and the two versions share common building blocks (Howard, *et al*., 2019).

3.4.1 Structuring MobileNetV3 architecture

At its core, MobileNetV3 uses a novel architecture design that was based on a combination of complementary search techniques (Howard, et al., 2019). The core building block of MobileNetV3 is the inverted residual block, which consists of the following components: an expansion convolutional layer; depth-wise and point-wise convolution layers; a squeeze and excite layer; and a projection layer (Howard, et al., 2019) (Figure 1).

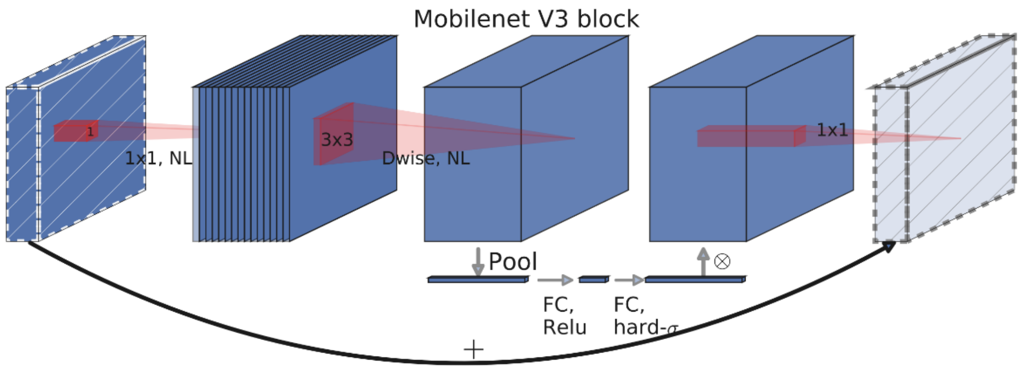

FIGURE 1: Structure of MobileNetV3 architecture (Howard et al., 2020)

For the expansion convolutional layer of the model, this layer expands the input channels to a higher-dimensional space where it is regarded as a key component to the architecture of MobileNetV3 (Howard, et al., 2019). Spatial dimensions are gradually reduced within the input channel of the model, whereas the map feature depth is increased. This allows for depth-wise expansion to capture a wide range of features, resulting in a more efficient and effective network (Alzubaidi, et al., 2021).

For the depth-wise convolutional layer, it is a type of convolutional layer that has a single convolutional filter for each input channel (Alzubaidi, et al., 2021). A standard convolution is decomposed into two separate layers known as; a depth-wise convolutional layer and a pointwise convolutional layer (Abubakar, *et al*., 2020). Depth-wise convolutions keep each channel separate, whereas compared to regular 2D convolutions mix channels (Habib & Qureshi, 2022).

The squeeze and excite layer within the model's architecture is used to process the output of a convolutional block by modelling the interdependencies of the channels (Howard, et al., 2019). This is done by essentially "squeezing" the convolutional output to one value per filter, which is known as average pooling, and bypassing the result through a series of linear and nonlinear layers and multiplying the result with the original input (Habib & Qureshi, 2022).

The projection layer of the model then projects features back to the desired output channel, where it uses a 1x1 filter that manages the number of feature maps (Howard, et al., 2019). The projection layer is referred to as a projection operation, feature map, or channel pooling layer, where the projection layer maps discrete word indices to a continuous vector space (Alzubaidi, et al., 2021).

3.4.2 MobileNetV3 Model

The model is a 2D convolutional sequential model that stacks linear layers within Keras Tensorflow, where one input tensor and one output tensor are made for each layer (Keras, 2023). Sequential models are useful for building deep learning models such as feedforward neural networks (Keras, 2023). Max pooling is used as a function for the model to reduce the spatial dimensions of the input volume for the next layer (Glegola, et al., 2021). The MaxPooling2D layer down-samples the input along its spatial dimensions by using the maximum value over an input window for each channel of the input (Glegola, et al., 2021). The model uses pre-process functions from Keras Tensorflow to pre-process the images into a format that the model can use to make deductions. The pre-processing layers of the Keras Tensorflow API allow developers to build Keras-native input processing pipelines (Keras, 2023). The input processing pipelines can be used as an independent pre-processing code in non-Keras workflows, combined directly with Keras Tensorflow models, and exported as part of a Keras Saved Model (Keras, 2023). The heights and weights of the images are set to 224, respectively, with a batch size of 32 images, with the input tensor of the model being a 1D array. A small batch size was used instead of using single image processing to improve the efficiency, generalization, and stability of the model. By processing multiple images simultaneously instead of processing images one by one, training speed can be increased due to the computations on the GPU being parallel (Alzubaidi, et al., 2021). In addition, small batch sizes offer better accuracy estimates that lead to better generalization from the model (Kandel & Castelli, 2020). If a large batch size is used, then a batch normalization function is required to normalize the inputs of each layer to allow for stability and faster convergence within the model (Alzubaidi, et al., 2021).

The model uses 3600 images from the total 4000 images available for training, and 400 images from the total 4000 images for validation. The model has 11,540 trainable parameters, with 939,120 non-trainable parameters. The model was trained for ten epochs, where each epoch of training lasted 33 seconds. Figure 2 represents the summary of the model. The metrics used to benchmark the model on the Wadaba dataset are accuracy and loss. The accuracy of the model corresponds to the correctness of the value, where loss is the prediction of how erroneous the model's predictions are, and this loss value is calculated using a loss function (Chazhoor et al., 2022).

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 224, 224, 3)]     0

 sequential (Sequential)     (None, 224, 224, 3)       0

 MobilenetV3small (Functiona  (None, 7, 7, 576)        939120
 l)

 global_average_pooling2d (G  (None, 576)              0
 lobalAveragePooling2D)

 dropout (Dropout)           (None, 576)               0

 dense (Dense)               (None, 20)                11540

=================================================================
Total params: 950,660
Trainable params: 11,540
Non-trainable params: 939,120
_________________________________________________________________
```

FIGURE 2: Model summary

The images that are used for training and validation are augmented to increase the diversity of the training dataset by applying random transformations to the original data. To prevent overfitting, data augmentation is used to improve the generalization process of the model. Whereas Keras Tensorflow provides several functions for data augmentation. Some of the functions provided include resizing, rescaling, random flipping, and random rotation of images (Keras, 2023). Table 2 represents the number of images we have for training in their respective plastic resin code classes. Figure 3 is an example of the different types of plastics within the Wadaba dataset.

Training accuracy refers to the percentage of correctly classified images within the dataset (Alzubaidi, et al., 2021). It is a measure of how well the model is learning from the training data within the dataset. Training loss is the metric used to determine how well the model fits the training data (Habib & Qureshi, 2022). It is used to assess the level of error the model has on the training data.

Validation accuracy refers to the model's accuracy in evaluating the validation dataset (Alzubaidi, et al., 2021). The validation dataset is used separately from the training dataset, which is used to assess the level of generalization the model has (Alzubaidi, et al., 2021). Validation loss is the evaluation metric used to determine the performance of the model on the validation dataset (Habib & Qureshi, 2022). It is used as an assessment to determine whether the model is overfitting/underfitting.

TABLE 2: PET- Polyethylene terephthalate; PE-HD- high-density polyethylene; PVC- polyvinyl chloride; PE-LD- low-density polyethylene; PP- polypropylene; PS- polystyrene.

Resin Code	Class	Number of images
1	Polyethylene Terephthalate	2200
2	High-Density Polyethylene	600
3	Polyvinyl Chloride	0
4	Low-Density Polyethylene	0
5	Polypropylene	640
6	Polystyrene	520
7	Other	40

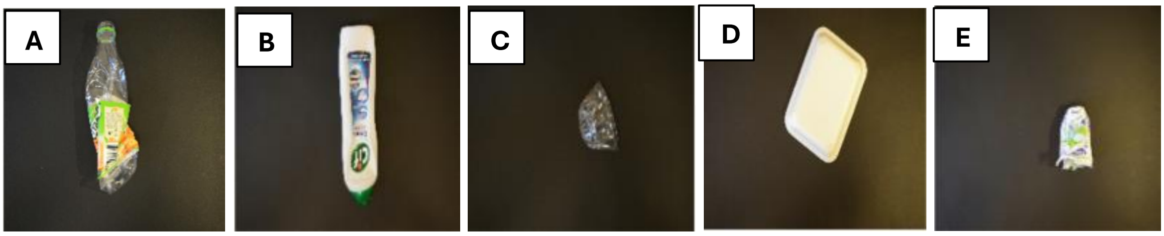

FIGURE 3: Examples of different types of plastics from the WaDaBa dataset: **A**, PET (polyethylene terephthalate, 1); **B**, PE-HD (high-density polyethylene, 2); **C**, PP (polypropylene, 5); **D,** PS (polystyrene, 6); **E,** Others (7)

4. Results & Discussion

The algorithm that was developed was based on the previous model of MobileNetV2, but it uses the MobileNetV3-Small architecture for faster image processing and recognition. It is important to note that previous research was done by Bobulski & Kubanek (2021), on both MobileNetV1 and MobileNetV2, which achieved accuracy scores of 80% and 86%, respectively, for recognizing and predicting the Wadaba dataset. The MobileNetV3-Small architecture uses already available data to improve plastic waste image classification on the Wadaba dataset. With regards to training, the model used an image width and height of 224 pixels respectively, with 4000 image files belonging to 20 classes, and 3600 files used for training.

The model's accuracy and loss at plastic image recognition were compared by using three different learning rates to determine which learning rate is optimal for the Wadaba dataset. The model's three learning rates were set at 0.0001, 0.001, and 0.01, respectively, to see how efficient the model was at learning and recognizing the dataset. For a learning rate of 0.0001, the model has an initial loss of 3.87 and an initial accuracy of 3%. The training and validation loss per epoch is given in Figure 4.

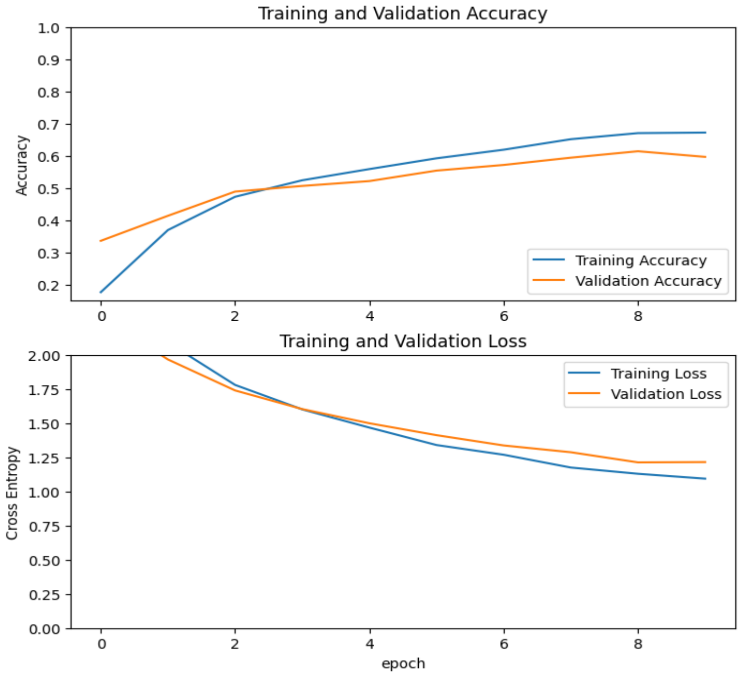

FIGURE 4: Training Loss, training accuracy, validation loss, validation accuracy for leaning rate 0.0001 for ten epochs of training

After training, the model achieved a training accuracy of 67.2% and a validation accuracy of 59.7%, with its training loss at 1.09 and a validation loss of 1.21. This indicates that the model is recognizing and learning the dataset at 60% accuracy with its learning rate set at 0.0001.

For a learning rate of 0.001, the model has an initial loss value of 3.71 and an initial accuracy of 5%. Figure 5 below represents the training and validation accuracy and the training and validation loss of the model at a learning rate of 0.001 after training. The model achieved a training accuracy of 67.1% and a validation accuracy of 61.7%, with its training loss at 1.10 and a validation loss of 1.21. This indicates that the model is recognizing and learning the dataset at 61% accuracy, 1% more efficient in comparison to the model set at a learning rate of 0.0001.

FIGURE 5: Training loss, training accuracy, validation loss, validation accuracy for leaning rate 0.001 for ten epochs of training

For a learning rate of 0.01, the model has an initial loss value of 3.71 and an initial accuracy of 5%. Figure 6 represents the training and validation accuracy and the training and validation loss of the model at a learning rate of 0.01 after training. The model achieved a training accuracy of 67.1% and a validation accuracy of 61.7%, with its training loss at 1.10 and a validation loss of 1.21. At this learning rate, the model is 61% accurate at recognizing the dataset. The model is of the same performance as that of a learning rate of 0.001, highlighting that the model is more optimal and efficient at recognizing and learning the dataset at either a learning rate of 0.001 or a learning rate of 0.01 in comparison to the model set at a learning rate of 0.0001.

FIGURE 6: Training loss, training accuracy, validation loss, validation accuracy for leaning rate 0.01 at ten epochs of training

The comparison of the three different learning rates was to indicate which learning rate is optimal for the model to train. To support this, an evaluation of the model's accuracy at the three different learning rates was conducted to compare which learning rate is optimal. This was done by using the function model.evaluate() to calculate the loss and accuracy of the model after it has been trained on the Wadaba dataset for ten epochs. Table 3 represents the model's accuracy evaluation at learning rates of 0.0001, 0.001, and 0.01.

TABLE 3: Model's accuracy evaluation at learning rate 0.0001, 0.001, and 0.01.

Learning Rate	Accuracy	Loss	Time (seconds)	Step (ms/step)
0.0001	0.59	1.21	3	171
0.001	0.61	1.21	3	181
0.01	0.61	1.24	3	178

For the evaluation of the model's accuracy at a learning rate of 0.0001, the model has an accuracy of 59% and a loss of 1.21. At a learning rate of 0.001, the model has an accuracy of 61% and a loss of 1.21. At a learning rate of 0.01, the model has an accuracy of 61% and a loss of 1.24.

Object detection algorithms need extensive datasets to compare current algorithms and support the advancement of visual comprehension (Tamim, et al., 2023). This advancement is crucial as algorithms continue to be developed for realistic scenarios (Tamim, et al., 2023). Deep learning algorithms demand a dataset that is extensively annotated, however, the most significant limitation of deep learning algorithms is the lack of annotated datasets for real-world plastics (Majchrowska, et al., 2022). Single-object images have been replaced by instance-level segmentation (Majchrowska, et al., 2022). Whereby this segmentation creates a challenge for object detection due to the availability of extensive annotated datasets (Majchrowska, et al., 2022). These datasets cannot be developed by using existing images from the internet, the images need to be captured (Majchrowska, et al., 2022).

Having a diverse dataset is crucial due to the reality that plastic waste objects are not rigid and fixed and can be deformed in dramatic ways. When plastic waste starts to degrade, only small areas of the object are visible, and under different lighting conditions, plastic waste objects can display various colours and different pixel values (Tamim, et al., 2023). The changes in pixel level will impact the accuracy of the deep learning model in terms of classifying and detecting objects of interest (Majchrowska, et al., 2022). Convolutional neural network-based detectors are often trained on datasets that only contain images that are well-exposed, with little to no images that were taken under difficult lighting conditions (Tamim, et al., 2023). Plastic waste within a natural setting is present within landfill sites, oceans, and public spaces such as parks. Where there is a crucial need to capture plastic waste with various natural backgrounds to further the dataset in true detail, and to further test the capabilities of existing deep learning models to develop more efficient and effective models for plastic waste identification with minimal biases (Majchrowska, et al., 2022).

When compared to previous research done by Bobulski & Kubanek (2021), and Chazhoor *et al*. (2022) that used the Wadabba dataset, the results obtained from this experiment are satisfactory given the stage of this research, with a general accuracy score of 60%. However, compared to the research of Bobulski & Kubanek (2021), their CNN achieved an accuracy of 72%. The difference lies in the type of CNN that was used. This experiment made use of the MobileNetV3-Small architecture, whereas Bobulski and Kubanek (2021) developed their own CNN with fewer parameters that can run on a microcomputer that uses the Raspberry Pi platform.

According to Chazhoor *et al.* (2022), their experiment achieved an accuracy score of 87.44%, where the difference in their experiment was due to the use of the ResNet architecture that uses the ResNet 50-50 repeating layer strategy. In comparison to the MobileNet architecture, the ResNet architecture offers higher accuracy with the trade-off being speed (Chazhoor *et al.*, 2022). Whereas MobileNet offers lightweight real-time object detection, that is more suitable for devices that are resource-constrained (Glegola, *et al.*, 2021).

In comparison to Thiagarajan (2020), their research achieved high accuracy scores of 93.4% for plastic bottle detection. The difference lies in the number of images they used for their research. Their dataset contained 16,200 images, whereas this study made use of the Wadabba dataset, which contains 4000 images. Thus, their network was exposed to four times the amount of images for its training and validation process, making it more accurate for classification. By having a large dataset, the CNN will be able to learn more features that it can distinguish and generalize well due to the dataset being large in size and diverse. As a result, a large dataset can reduce the risks of overfitting or underfitting. The network is also capable of handling data that it has never seen before due to having many examples that it can validate (Majchrowska, *et al.*, 2022). By having a small dataset, the risk of overfitting is high, where the network will result in poorer performance due to the network only memorizing the training dataset instead of learning patterns that are distinguishable, and not being able to generalize well as a result.

Having a large dataset is also evident in the research done by Uganya *et al.*, (2022), where their system achieved an accuracy of 92.15%. This is attributed to the implementation of the Internet of Things (IoT) within their system design. This allows their system to connect and exchange data with other systems and devices through the internet. By doing so, their network can learn from other systems and devices, further increasing its ability to learn general patterns and being able to generalize well.

When compared to other developing countries, the system developed by Abubakar *et al.*, (2020), achieved an accuracy score of 98% for the classification and separation of waste. Their system was developed using the SmartPLS software for statistical analysis. The results from this experiment differ from the results of Abubakar *et al.*, (2020) since the data from this experiment was not imported into the SmartPLS software. The model of this experiment was developed using the MobileNetV3-small architecture by using the Keras TensorFlow open-source library that uses the Python interface for artificial neural networks. SmartPLS is a software that has a graphical user interface that is meant to structure equation modelling by using the Partial Least Squares (PLS) path modelling method (Abubakar *et al.*, 2020). SmartPLS was not used for this model since it was not deemed complex. This was done to ensure the model's integrity for operating on resource-constrained devices such as mobile devices.

The research done by Devi *et al.*, (2018), achieved scores of 94% and 82% respectively for waste object detection. In comparison with the results of this experiment, the difference is that a protocol buffer was not used for this experiment to either serialize or deserialize the weights of the model. The reason is that this experiment made use of transfer learning, freezing the hidden layers within the model, thus, the model's weights were not updated.

A higher accuracy indicates that the model is learning at a learning rate that is optimal for the dataset that was given for training and validation, and can generalize well from it. It pertains to the learning effectiveness of the model, where the model can learn and identify underlying patterns within the dataset at an effective rate. This means that the model is improving its performance within each epoch of training with minimal solutions that are suboptimal at a learning rate of 0.001.

If the learning rate is too low for the model, as is the case with a learning rate of 0.0001, the model may learn at a slow pace and might not be able to capture the underlying patterns that exist within the dataset by using fewer epochs for training. As a result, underfitting would occur where, due to training accuracy being low and validation accuracy being low, the model will struggle to consistently classify the data it was trained on.

If the learning rate for the model is high, as is the case with a learning rate of 0.01, the model may learn too quickly from the dataset it has been given. As a result, a high learning rate may lead to potential instability, and oscillation may occur around optimal solutions (Alzubaidi, et al., 2021). The model may tend to overshoot its optimal parameters during the training process, which can lead to overfitting and high variance. Such is the case with previous work done by Thiagarajan (2020), where 600 images were used, at a size of 64x64, for 50 epochs of training. Even if increasing the dataset size, the images used were highly correlated due to augmented samples being used for the input (Thiagarajan, 2020). As a result, overfitting occurred within their research, but this was solved by modulating the entropy capacity of the neural network (Thiagarajan, 2020).

If the learning rate for the model is optimal, as is the case with a learning rate of 0.001, the model is deemed stable and can converge effectively toward an appropriate solution without experiencing overfitting or underfitting. The gradient of the model is not deemed too large or too small, which enables the model to update its parameters in a manner that is controlled. As a result, the model will be able to reach high-performance levels in fewer training epochs and use fewer computational resources, making it suitable for mobile CPUs. This is evident within the research done by Bobulski and Kubanek (2021), whereby using a MobileNet network of 15 layers, the network was better structured due to better generalizing properties. This was due to the use of fewer features for recognition, which makes it possible to use images of smaller sizes that have more features that are useful and less noise within the image

(Bobulski & Kubanek, 2021). The number of layers, which translates to the number of features for recognition, influences the number of parameters of the model, whereas according to Glegola, et al., (2021), a neural network with fewer parameters has an advantage for implementation on mobile operating systems.

5. Conclusion

The use of transfer learning has been shown to be significant in optimizing the model's accuracy score, which is favorable at 60% in recognizing and predicting the Wadaba dataset at three different learning rates. The reason why transfer learning was used is due to the large amounts of data needed to optimize the accuracy of the MobileNet network. This data needs to be trained on a powerful Graphical Processing Unit for hours to obtain results. However, using transfer learning can reduce the learning process of a neural network by reducing the computational load that is needed for the model.

This was achieved by using the already pre-trained architecture of MobileNetV3-Small, which would allow the network to be more compatible with mobile devices and offer a higher accuracy score of 6.6% compared to MobileNetV2 (Glegola, *et al.*, 2021). The architecture of MobileNetV3 offers new and efficient versions for nonlinearities that are more suitable for mobile devices and settings (Glegola, *et al.*, 2021). Where this efficiency is maintained, and the new and improved versions of nonlinearity can be used to improve performance (Howard, et al., 2019). Thus, MobileNetV3 does offer a solution for the ease of access to information due to real-time applications such as image recognition and classification without using extensive computational resources (Howard, et al., 2017).

Within the experimental stage of this research, the MobileNetV3-Small model was found to, on average, have an accuracy score of 60% in recognizing and predicting the Wadaba dataset at three different learning rates. This highlights that the model is capable of recognizing and predicting the dataset at an accuracy that is satisfactory, considering the stage of this research. However, in comparison to previous research, accuracy would need to be improved for the MobileNetV3-Small network to be consistent in recognizing and comparing the Wadaba dataset. This can be achieved by reducing the depth of the model, as mentioned by Bobulski & Kubanek (2021), where their models for MobileNetV1 and MobileNetV2 are 15-layer models each. This will reduce the overall complexities within the model, as well as reduce computational load. The use of diverse datasets will also improve the accuracy of the model, where the model would be able to learn and generalize well due to being exposed to a dataset that has more significant features.

The main difference between this experiment and previous experiments is that previous experiments had access to datasets that were diverse and large in size, compared to the dataset of this experiment. By having a large dataset, overfitting will be reduced within the MobileNetV3-Small model, and the model will be able to learn more patterns that are generalizable due to having access to a dataset that is more diverse. As mentioned by Majchrowska *et al.*, (2022), datasets that are not of the same quality can hinder the fair and valid comparison of methodologies. Where reported research uses different datasets, metrics that are incoherent, and the use of data splits that influence results (Majchrowska, *et al.*, 2022)

MobileNetV3-Small operates efficiently and is suitable for mobile devices and the settings thereof. Improving the accuracy will allow the MobileNetV3-Small network to be more fine-tuned and compatible with mobile devices, which will allow mobile devices to be able to recognize plastic waste without using extensive computational resources and provide the user with a decision on how to dispose of this waste. Given the results of this research, CNNs such as MobileNetV3 can identify plastic waste, where the development of this CNN can be used to facilitate the need for information that is accessible. For the human component, having information that is accessible can be a driver of change, where pro-environmental behaviour, such as recycling, will be influenced due to available support. Individuals will be able to use this technology due to its ability to operate on resource-constrained devices. By doing so, information will be made available to individuals in real-time to allow them to make informed decisions on how to dispose of their plastic waste. By making information available, individual behaviour and habits will be influenced in a manner that is sustainable toward the environment. At an individual level, household plastic waste will be managed sustainably since individuals are more informed on what action can be taken. Thus, MobileNetV3 can be used to facilitate the ease of access to information for the public to facilitate better plastic waste management practices.

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Appendix 1

TABLE 1: Different types of plastics, uses, properties, and recycled into

Resin Code	Type	Uses	Properties	Recycled into
1	Polyethylene terephthalates	Containers, water bottles, soft drink bottles, etc. (Alabi, *et al*., 2019)	Softens at 80°C, transparent, strong, resistant to solvents. (Alabi, *et al*., 2019)	Soft drink bottles, building insulation, clothing, etc. (Alabi, *et al*., 2019)
2	High density polyethylene (HDPE)	Crates, buckets, detergent bottles, milk bottles, etc. (Düşünceli & Colak, 2006)	Semi-flexible to rigid, non-transparent, softens at 75°C, moisture resistant (Düşünceli & Colak, 2006)	Compost bins, recycling bins (Düşünceli & Colak, 2006)
3	Polyvinyl Chloride (PVC)	Plumbing pipes and fittings, garden hose, bottles, (Alabi, *et al*., 2019)	Strong, can be transparent, can be solvent welded, and softens at 80°C (Alabi, *et al*., 2019)	Compost bins (Alabi, *et al*., 2019)
4	Low density polyethylene (LDPE)	Cling wrap, squeeze bottles, refuse bags, garbage bags (Barbosa, *et al*., 2017)	Soft, flexible, scratches easily, translucent, and softens at 70°C (Barbosa, *et al*., 2017	Pallet sheets, bin liners (Barbosa, *et al*., 2017)
5	Polypropylene (PP)	Straws, lunch boxes, kettles, packaging tape, microwave dishes, potato chip bags, bottles, and ice cream tubs (Maddah, 2006)	Hard, translucent, solvent resistant, versatile, softens at 140°C (Maddah, 2006)	Pallet sheets, pipes, bins, and pegs (Maddah, 2006)
6	Polystyrene (PS)	Foamed polystyrene cups, protective packaging, CD cases, imitation glassware, plastic cutlery (American Chemistry Council, 2014)	Non-transparent, semi-strong, resistant to alkalis and salt solutions, but affected by fat, acids, and solvents, it has low water absorption, when not pigmented it is transparent, and softens at 95°C (American Chemistry Council, 2014)	Recycle bins (American Chemistry Council, 2014)
7	Other	Computer electronics, packaging, cooler bottles, automotive and appliance components (Alabi, *et al*., 2019)	Properties are dependent on the type of plastic or combination of plastics used, including all resin and multi-materials, for example, laminates (Alabi, *et al*., 2019)	Recycle bins (Alabi, *et al*., 2019)