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Machine Learning-Based Automatic Litter Detection and Classification Using Neural Networks in Smart Cities

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ABSTRACT

Machine learning and deep learning are one of the most sought-after areas in computer science which are finding tremendous applications ranging from elementary education to genetic and space engineering. The applications of machine learning techniques for the development of smart cities have already been started; however, still in their infancy stage. A major challenge for Smart City developments is effective waste management by following proper planning and implementation for linking different regions such as residential buildings, hotels, industrial and commercial establishments, the transport sector, healthcare institutes, tourism spots, public places, and several others. Smart City experts perform an important role for evaluation and formulation of an efficient waste management scheme which can be easily integrated with the overall development plan for the complete city. In this work, we have offered an automated classification model for urban waste into multiple categories using Convolutional Neural Networks. We have represented the model which is being implemented using Fine Tuning of Pretrained Neural Network Model with new datasets for litter classification. With the help of this model, software, and hardware both can be developed using low-cost resources and can be deployed at a large scale as it is the issue associated with healthy living provisions across cities. The main significant aspects for the development of such models are to use pre-trained models and to utilize transfer learning for fine-tuning a pre-trained model for a specific task.

KEYWORDS

Litter Detection and Classification, Machine Learning, Neural Networks, Smart City

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INTRODUCTION

One of the simple, yet significantly complete definitions of smart cities is the one given by Eduadro Paes (2013), which goes like this: “Smart Cities are those who manage their resources efficiently. Traffic, public services, and disaster response should be operated intelligently to minimize costs, reduce carbon emissions and increase performance.”

The last decade has seen many technologies, meant for smart cities (2022). In the past two decades, smart city solutions have emerged, enabled by technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Deep Learning, and Cloud Computing. They offer vast potential to address infrastructural, societal, and pandemic challenges. With smart technologies, communities can improve energy distribution, streamline trash collection, decrease traffic congestion, improve air quality, and more with help from smart, connected sensing systems (Tay & Mourad, 2020; Thoumi & Haraty, 2022).

The Cities represent a composite structure of social and economic entities and the center of data, employment and trade, and significant foundations of authority. In 2030, India expects 40% of the entire population to house in cities, and thus will subsidize above 70% of the nation’s GDP. Therefore, cities require the necessary equipment for social and physical infrastructure to deliver quality life and economic prospects to the urban population reasonably and sustainably (Arasteh, 2016).

In today’s scenario, Cities are turning into money-spinners of data by producing huge quantities through video cameras, traffic control systems, sensors, vehicles, smart meters, mobile phones, and IoT devices. Moreover, the historic data is already gathered in manual form or in automated forms for enabling supervised learning. The developing technologies, such as Artificial Intelligence (AI), Machine learning (ML), and Deep learning (DL), can reform the challenges related to the exponential data growth due to smart cities. AI and ML devise the potential to turn vast data into a meaningful form and practice the learned intelligence for improving the performance, and optimization of the operational resources and their cost factors, enabling proactive citizen arrangement, consequently creating cities liveable and efficient. With the capability to connect with older data handling systems, AI has the power to produce much-desired insights for the functioning of smart cities (Peñalvo et al., 2022; Samir et al., 2019; Taleb & Abbas, 2022). Therefore, with the help of resources urbanized by Smart Cities Operation and the composite changing aspects of the urban environment, smart cities stand to assistance by AI Implementation. AI has several applications, from sustaining an improved atmosphere to improving transport for the public along with management of all the safety parameters. Nowadays, even the Government is enthusiastically assisting the deployment of AI-driven services to produce smarter cities. Some of the applications where AI is already used are highlighted below:

- **Automatic Traffic Control:** In the US, several cities use automatic traffic control systems to control various intersections to moderate travel time and waiting time over the signal.
- **Conversational Chatbot:** In Singapore, an agency developed a chatbot to make public websites more accessible for citizens, conversational Chatbot will be responding in natural language for seamless interaction.
- **Tracking Disease:** In Canada, Bluedot implemented ML and NLP-based schemes for tracking, identifying, and reporting the spread of viruses very quickly. This scheme may lead to developing the technology to predict infection risks to humans in near future.
- **Gathering Management:** India implemented AI proficiencies in Kumbha Mela, where gathering happens in huge amounts and 1000 CCTV covers an area of approx. 3200 hectares. With the help of AI, administrators can identify suspicious activity in gathering.
- **Facial Attendance:** Tamilnadu’s (India) government has applied AI-based systems to mark everyday attendance by recognizing a face and thereby reducing the time to mark attendance, since 2019.

- **AI-Driven Sowing:** AI-driven sowing application has been developed by the AP government in collaboration with Microsoft for quality and efficient farming in India. The Application will help to predict all the necessary parameters for better farming.
- **Public Service Delivery:** The IT department of Telangana state, is utilizing AI features for extracting all necessary public services such as government offices, marriage fees, property registrations, and many more. Most of the inquiry calls are related to basic services and repeat questions, so, the chatbot will be working perfectly fine for such applications.
- **Improvement of the Education System:** The UP government has already started a plan to implement AI bots for up gradation of the system, considering staff shortage and making the education system corruption-free as well as less neglectful.
- **Improving Highway Safety:** To improve road safety, AI-enabled buses and vehicles will be more helpful for sleepy drivers and collision avoidance.

The range of applications of machine (Singh et al., 2022) and deep learning for smart cities / smart living is tremendous and requires categorization for a systematic study. In most of the literature related to the planning of smart cities, the domain includes the following 6 areas: (i) smart governance, (ii) smart economy, (iii) smart mobility, (iv) smart environment, (v) smart people and (vi) smart living. For smart cities, one can broadly classify the ML/DL applications into respective application areas including (a) Issue / Complaint resolution and accountability, (b) Production/ Service Sector Growth (c) Traffic / Parking (d) Infrastructure (Highways, Roadways, Buildings – Pollution Issues, Smog, etc.), (e) Healthcare, especially for Kids and Old-aged, and (f) Safety and Security issues. We will mostly concentrate on the detailed analysis of particular case studies which correspond to the representative class of applications. A formal introduction of smart city descriptions is presented, which gives a framework for understanding the usefulness/criticality of classes of applications as indicated in (a)-to-(f). It is important to outline that the subject of Smart Cities Panning and its evaluation of its performance (smartness) is an interdisciplinary subject. The maturity models are mostly documented in the form of Performance Measure (PM) in the literature. The progression of such models can be tracked from 2007, wherein the key parameters are mostly those which are the problems/issues faced by non-smart city residents. The widely accepted framework now is the one that is accepted and used by the Government of Australia (the Year 2017). It includes along with others, the key parameters like (a) Jobs and Skills (b) Infrastructure and Investment (c) Liveability and Sustainability (d) Innovation and Digital Opportunities (e) Governance, Planning, and Regulation, and (f) Housing. As indicated, the representative class of applications will be discussed in the context of the machine learning (Almomani et al., 2022) approaches over datasets. We try to make the analysis as accurate as possible. We discuss the implementation of the proposed ML/DL techniques using the open data sets available on Kaggle/ other open sources.

Modern Applications of Machine Learning for Smart Cities

Urbanization is a common demographic trend, for ages, which we can observe very well. However, “urban” refers to the presence of several features which distinguish it from so-called “rural” regions. In the jargon of new and innovative ideas in technology and our everyday life, the idea of smart cities is comparatively new. Still, there is no well-accepted definition of a smart city, thus making this term vague and fuzzy. We can accept the definition of a smart city as one which makes use of smart technology, and thus, has smart people. The term “smart city” is a broad term having several parameters, the most common of them are tabulated Table 1.

Maturity Models for Smart City

The term Maturity, in the context of a system, refers to a precise, radical and advanced development form of the state of a system. In terms of management viewpoint, it generally denotes the levels by which an organization improves its internal processes. Röglinger et al. (Igartua et al., 2018; Wendler,

Table 1. Smart city areas

Area	Description	Actions
Smart Governance	Rules, regulations, and enforcement so that the entire city can function hassle-free and effectively.	Online Public Services Electronic Voting Transparent Governance Value Added Services Online Services E-governance
Smart Economy	E-business and E-commerce ICT-enabled smart delivery of services- Online Education System ICT-based Innovative Services	Design strategies for economic growth Tax Payment Systems Meticulous use of ICT in business
Smart Mobility	Integrated Transport and Mobility Systems.	Safe Transport Smart Vehicles Accident Proof Cars Mobile Internet Smart Traffic and Parking Systems
Smart Environment	Renewable Energy, Optimizing Energy Efficiency in existing systems, Smart product designs	Pollution Reduction Design enforcement Promotion of E-vehicles Plantations Solid Waste classification and disposal
Smart People	ICT skilled people. ICT enabled working, Innovation in every aspect. Minimizing redundant actions and tasks	Existence of University, Knowledge Centers. Digital amenities, Planning based on research, development, and innovation.
Smart Living	ICT-based life Styles, behavior, and consumption.	Health Insurance / Life Insurance for one and all. Mandatory Education for all. Child labor prevention etc.

Source: Adapted from European Parliament (2014) and ITU-T (2014)

2012) suggest the maturity models drive just like tools for estimating the grade of advancement in different sectors and generating achievement strategies to develop the administration's existing level to stretch and achieve all the objectives. To sum up, the maturity model represents "the extent of the rise in the development of a society which signifies the level of success and effectiveness of the body" (Firmanyah, Supangkat, Arman, & Adhitya, 2017). We must follow several levels to build a maturity model for a particular society. The primary level or stage is deciding the scale that will be deployed and used. The processing and controlling specialisms are inadequate or vague at a lower level of the system, but on higher levels which are fixed few processes lead to an optimal execution. A huge number of maturity models are already present such as Quality models, Business process models, Strategic alignment models Maturity Models for Human factors, etc., all of these have a common objective due to a similar target to assess the present status in a group to enable benchmarking as well as to provide a guiding principle for enhancement (Wendler, 2012). For maturity representation, the levels generally start from 0 to 5 using different nomenclature (Wendler, 2012). The five levels of strategic alignment maturity models are shown in Figure 1.

In the domain of software development, a reputed model is Capability Maturity Model (CMM) which was developed in 1986 by the Software Engineering Institute (SEI) (Waarts, 2016). The main purpose to launch CMM aimed at the measurement of maturity for the under-development software processes thereby achieving all the quality goals (Torrinha & Machado, 2017). The five levels of CMM can be represented in Figure 2.

Depending on the domain where we have to apply maturity models, multiple ways may be followed to compare and select one suitable. In (Almomani et al., 2022; Guédria et al., 2008; Khoshgoftar & Osman, 2009; Man, 2007; Pöppelbuß & Röglinger, 2011; Proença et al., 2016; Singh

Figure 1. Levels of strategic alignment maturity models

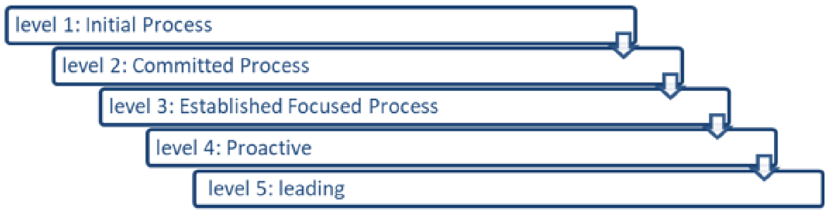
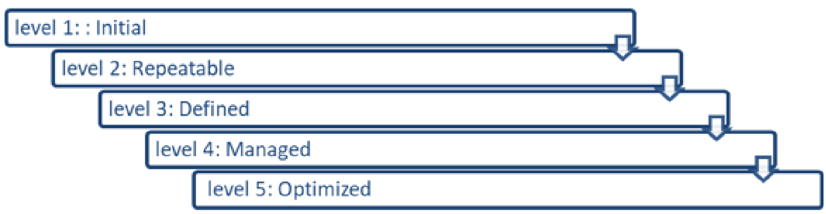


Figure 2. Levels of strategic alignment maturity models for organizations



et al., 2022) authors have suggested multiple methods for the comparison of various maturity models correspondingly. In (Khoshgoftar & Osman, 2009), the author provides a relevant comparison of nine different maturity models based on 27 different nominated variables such as Organization Strategic, Date of Issue, Number of Maturity levels, Reference to Standard, Publisher, Project Management Process, Scope, Level, Discrete and Continues, Details, Definition of Maturity, etc. Likewise, in (Man, 2007) author proposes a model for the comparison of project-based models and management systems. The criteria for a rating of this framework may be listed as follow: Publication, Method independence, Transparency, Public domain, Industry independence, etc. In (Guédria et al., 2008), the authors proposed the model for interoperability domains, such as EIMM, LISI, SPICE (ISO/IEC 15504), OIM, and LCIM. A tentative comparison has also been represented as per the contextual foundation behind all the chosen models by the developer such as Interoperability concerns, Interoperability potential properties, Interoperability approaches, and Interoperability barriers. What common design principles must be employed for maturity models in a particular application area? Later after getting an extensive review of the literature, it was concluded that a framework may follow several design principles for deciding on a standard maturity model (Proença et al., 2016). The conclusion revolutionized this domain and the researchers broadly took the proposed framework for their model (Clarke, 2013; Lee et al., 2014). Due to its comprehensiveness, this research used it to compare the selected Smart City Maturity model that will be discussed in more detail as follows.

Pöppelbuß and Röglinger (2011) offered distributed the framework of maturity models for the common design principles (DPs) into three groups following the design principles. All the considered DPs demonstrate simple principles, descriptive principles, and prescriptive principles. It is very significant to identify that every maturity model do-not require to meet all DPs. Alternately, the objective of the model needs support from experts and investigators to compare current maturity models. This can be referenced as a checklist for designing the new maturity models.

Existing Smart City Maturity Models (SCMM)

As mentioned earlier, several maturity models have been proposed so far for various domains, Smart cities is one among them. Maturity models for Smart Cities are primarily aimed at helping the leaders to examine the city's recent state and support its evolution by providing guidance. The existing Maturity models for a smart city are as follows:

1. Smart City Governance Maturity Framework (2012)
2. IDC Smart City Maturity Model (2013)
3. Smart City Readiness (2014)
4. Smart City Maturity Model (SO SCMM) by Sustainability Outlook (2014)
5. Maturity Model for Measuring and Comparing Inequality in Brazilian Cities (BrSCMM) by Afonso et al. (2015)
6. Garuda Smart City Model (2017)

Table 2.

Maturity Model	Details	Domain	Maturity Levels
Capability maturity model (Pöppelbuß & Röglinger, 2011)	Purpose: The Model measures the maturity level for all processes along with Software development to attain quality goals for the organization. Scope: A scheme proposed with a key process area for guiding all those who need consistency in their projects. Focus: Complete developmental Processes	Can be changed by referring to the capability required to be Measured.	Initial, Repeatable, Defined, Managed, Optimized.
Smart City Governance Maturity Framework (Lee et al., 2014)	Purpose: The work offers a conceptual model referring to the general development of a Smart City Scope: A framework defined referring to Seoul, Amsterdam, and San Francisco. (3 Cities) Focus: Infrastructure along with Governance of the city.	Based on Municipal Ordinance, Smart City Leadership, Smart City Principles, Smart City Strategy Formulation, Smart, City Development /Management Process, Measurement Performance, Dedicated Organization,	1,3,5,7
IDC Smart City Maturity Model (Clarke, 2013)	Purpose: Suggests a scheme for evaluating the present situation of the city as well as a planning tool for adopting Smart City practices. Scope: Suggested a model for cities and local governments Focus: Applicable to city governance process and its enhancement	Smart Government, Smart Service, Smart Building, Smart Energy and Environment, Smart Mobility,	Ad hoc, Opportunistic, Repeatable, Managed, Optimized
Smart City Readiness (Scottish Cities Alliance, 2014)	Purpose: designed to walk cities through the process of clearly identifying the next steps, together with the investment and resources required to realize their ambitions. Scope: Applying the model toward important resource areas offered by the Scottish Government Focus: Cities' basic infrastructure and urban resilience	Governance and Services Delivery Models, Strategic Intent, Data, Technology, Citizen and business engagement.	ad-hoc, opportunistic, purposeful & repeatable, operationalized, optimized
Smart City Maturity Model (SO SCMM) by Sustainability Outlook (Business, 2014)	Purpose: Organizing a city referring a set of procedures Scope: Applying the model to the main source areas offered by the Government of India. Focus: Cities' basic infrastructure and urban resilience	Transport, Spatial Planning, Water Supply, Sewerage & Sanitation, Solid Waste, Storm Water Drainage, Energy & Electricity, ICT & Systems Intelligence, Economy & Finance, Environment.	Access, Efficiency, Behavior, and Systems Focus
Maturity Model for Measuring and Comparing Inequality in Brazilian Cities -Br-SCMM (Afonso et al., 2015)	Purpose: Measurement of all mechanisms and levels for improving economic and social policies for a city. Scope: Model suggested for the Brazilian cities Focus: Basic infrastructure as well as social terms and conditions of the city.	Technology, Housing, Energy, Water, Education, Governance, Environment, Security, Health Transport.	Simplified, Managed, Applied, Measured, and Turned
Garuda Smart City Model (Supangkat et al., 2018)	Purpose: Efficient implementation of Smart solutions for the government as well as citizen perception. Scope: Smart City development in Indonesia by referring to the proposed model. Focus: Relates to city improvement and its governance process.	Smart People, Smart Economy, Smart Infrastructure, technology, Smart Environment, Smart Governance, Smart Society	Ad hoc, Initiative, Scattered, Integrative, Smart.

Smart City Governance Maturity Framewor

This model is proposed in Korea for a fine evaluation of three cities: Seoul, San Francisco, and Amsterdam, by Firmanyah et al. (2017) in a study. The research objective focuses on applying smart practices in global cities to urbanize the process there. The focused parameters for this model are Urban Innovativeness, Smart City Governance, Intelligence & Sustainability, Smart City Infrastructure Integration, Service Innovation, Collaborative Partnerships, and Urban Openness. The research work accomplishes a Smart City maturity model for different practices (Lee et al., 2014). This model identifies four levels of maturity for determining smart city governance mentioned above in the table.

IDC Smart City Maturity Model

International Data Corporation (IDC) Maturity Model focuses on innovativeness to support measuring the current state and identifying the key abilities required for developing a Smart City. The model of IDC SCMM is stated in Waarts (2016). It managed to offer important phases of the framework to provide effective data and actions to support decision ability. Leaders or administrations may use this framework as a tool for developing a communal language, and improving cooperation for various groups for defining and implementing the key idea of Smart City policy thereby increasing the usage of modern smart City technologies. IDC identifies Smart metering cities into 5 main maturity levels and five key dimensions.

Smart City Readiness

This Model has been proposed and developed by the Scottish Government in collaboration with its local Cities Alliance, to access readiness by identifying the path, deciding the next step, and measuring the progress. It puts forward powerful yet simple techniques for the "targets" of smart cities to accomplish. Table 1 enlists the major five dimensions as well as five maturity levels measured by the proposed model. Along with the major five levels the model also supports three situations containing: 1) Administration of the city that defines the association of the unified system for city management. B) Status, which confirms the accessibility of data maintained by the city. C) Outcomes, that describe the results of the special impacts of Smart City (Scottish Cities Alliance, 2014).

Sustainability Outlook Smart City Maturity Model (SO-SCMM)

This Model has been proposed and developed by the Indian government to build a Resilient City to be successful enough to accommodate the Indian city's struggle and achieve urbanization. It represents 4 levels of maturity and provides ten important dimensions including systems intelligence, economy, water, and transport excluding some important parameters such as healthcare facilities, firefighting, and education (Clarke, 2013). The model SO SCMM effectively measures several indicators for the assessments of city status. Well-defined mapping indicators are listed along with a basic introduction to ISO 37120 standard.

The Brazilian Smart City Maturity Model (Br-SCMM) compares the Brazilian capital indicators, related to Urbanization. The model recommends a new specialized maturity model termed Br-SCMM for the measurement of the smart facilities provided by cities using a comparative study for five different stages. It considered ten major dimensions as well as smart indicators for level measurement starting from the first level to the fifth to identify the promising areas for upgrading before adopting various levels. A few studies reveal that the Br-SCMM model is the most suitable and comprehensive model due to its coverage of nine principles out of ten targeted.

The Garuda Smart City Model (GSCM) is designed and proposed by Smart City and Community Innovation Centre (SCCIC), by the Institute of Technology Bandung, Indonesia. GSCF was adopted by the Association of Indonesian Smart Initiative (APIC) as a model for Indonesia's Smart City. GSCF is a comprehensive framework that consists of the "Smart City Model", a measurement model.

ML Models for Clean City Initiative

One of the elementary aspects of smart cities is related to cleanliness and proper disposal of solid waste. Solid waste is commonly termed Litter. In further discussions, the terms Municipal Solid Waste (MSW) (Al-Jarrah & Abu-Qdais, 2006) and the term Litter are used interchangeably. In the subsequent subsections of this section, we discuss stepwise, several tools and techniques starting with a brief introduction to machine learning (Brdesee et al., 2022), deep learning, Computer vision, and the use cases of computer vision for litter classification and categorization. We also discuss the state-of-the-art techniques which are currently being used/proposed by researchers in the current domain. Finally, the most recently discovered EfficientNetBo- B7 models which use compound scaling for setting up model parameters, thereby achieving an efficiency of a remarkable 75% over top-5 ImageNet classes will be discussed. As and when required, the implementation code over Python is indicated for interested readers.

INTRODUCTION TO MACHINE LEARNING AND DEEP LEARNING

In a nutshell, one can specify Machine Learning (Yu & Reiff-Marganiec, 2022) as the applied area of Artificial Intelligence. Machine learning algorithms (Gaurav et al., 2022) can be broadly classified as those which are used for (1) Regression and (2) Classification (Loh, 2011). Regression refers to finding the value of a dependent variable based on two or more independent variables. A representative class of examples in this category includes (1) Dependence of Body Weight over Height of a particular demography (2) Price of House based on locality, number of Bedrooms, Sq. Feet Area, Amenities, etc. (3) Nutritional value of a Recipe based upon the nutritional components and quantity, etc.

Figure 3. Dependence of weight of person over height of the person

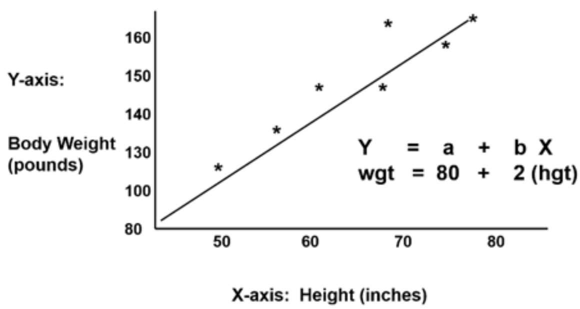
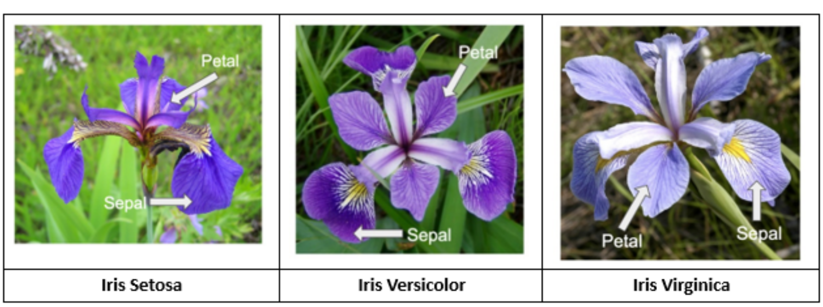


Figure 4. Iris flower species (Source: Kaggle, www.kaggle.com)



Classification refers to finding out the Class Label of a parameter based on the values of the independent variables. The most widely used example (The Hello World Example of Programming Language) is the Iris Flower Dataset Prediction. The four independent variables of this dataset are the measurements of sepal length, petal length, and petal width. The dependent variable is the class label which predicts the species of the iris flower, among one of the three species which almost look similar; namely Setosa, Versicolor, and Virginia. One another major dimension of the categorization of machine learning techniques is (1) Supervised Learning and (2) Unsupervised Learning. The methodology is called supervised learning if a dataset is available for training, having values of dependent variables (value or class label corresponding to regression or classification). In the case of no-training data, the machine learning technique falls in the Unsupervised Learning class. However, the majority of machine learning techniques fall in the category of supervised learning.

Out of several algorithms and techniques which are used in machine learning (Lv et al., 2022), the one that is mostly used for the solution of complex problems, like those of image recognition, natural language processing, etc., uses Neural Networks (Gurney, 2018). This domain of machine learning is called Deep Learning. Specifically, the term Deep Learning refers to those Neural Networks consisting of several hidden layers (that's why it's called Deep). The illustration of Artificial Intelligence, Machine Learning, and Deep Learning is shown in Figure 5.

In this section, we focus our discussion on Neural Network based machine learning techniques that have paved the way for revolutionary growth in the AI jargon. We particularly narrow down our discussion to convolution neural networks which form the backbone of image recognition and computer vision. We then discuss the state-of-art architecture of EfficientNet-B0 which uses compound scaling for performance optimization and gives remarkable efficiency over ImageNet in Top-1 classification.

Figure 5. Domain representation of AI, ML, and DL

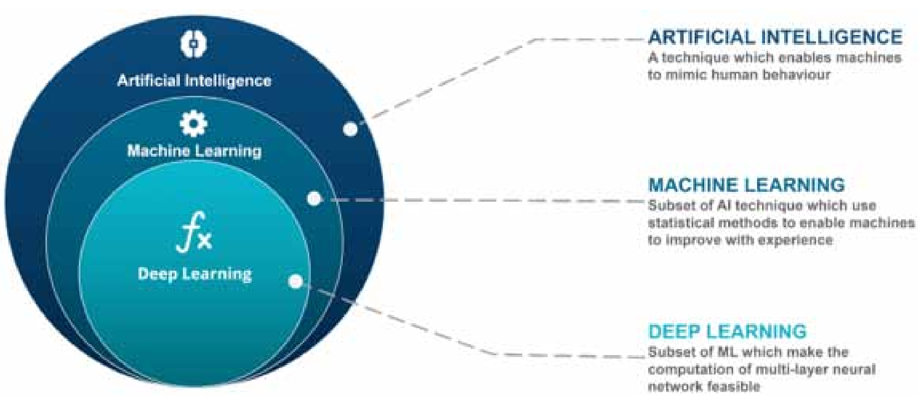
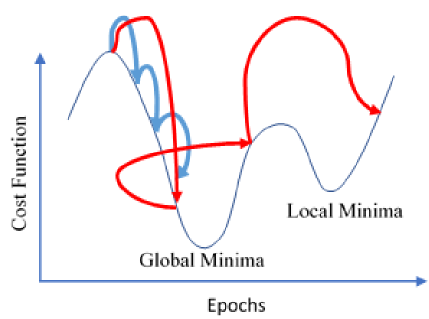


Figure 6. Iterative training of a model based on learning rate and the number of epochs



The BLUE color curves show the optimum gradient descent that will eventually lead to the global minimum. The RED color curves correspond to large values of learning rates that might not reach the global minimum. The COST FUNCTION is the Mean Square value, which is the summation of the squares of the distance between the observed and the predicted values. The training should proceed in such a way as to minimize the value of the cost function to its least possible value. In the general case of any machine learning model, a "Global Minimum" of MSE value can only be obtained using a suitable choice of Learning Rate, Epochs, and Optimized Backpropagation (Shankar et al., 2021). The accuracy of a machine learning algorithm is plotted against epochs, usually known as ROC (Receiver Operating Characteristics) curve, named for traditional reasons. A saturating value of accuracy is usually desired after a sufficiently large number of epochs. Neural Networks are brain-like models which make use of artificial neurons which are counterparts of biological neurons inside the human brain. A single neuron does a simple computation, but a massive network of such neurons can be trained to solve any problem which is (complex and still) beyond the scope of traditional computing. A representative class of such problems is Image Classification, Object Detection, and Computer Vision. A PERCEPTRON is one of the simplest ANN, the architecture of which is shown in Figure 7.

The model equation for the perceptron, in vector notation, can be written as follows:

$$Weighted\ Sum;\ Z = W^T \cdot X$$

$$Output;\ h_w\left(X\right) = step(W^T \cdot X)$$

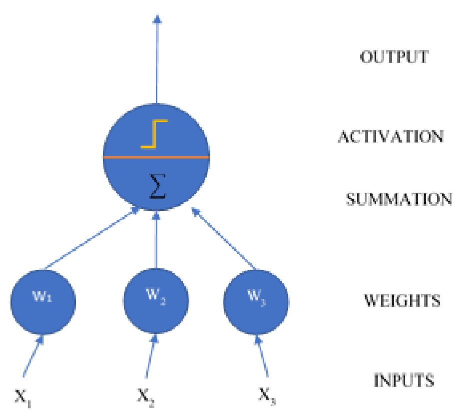
where the "step" is the step activation function.

In the case of a network in which there is a layered architecture with several neurons connected with weighted links, the learning equations (weight adjustment equations) can be defined as:

$$w_{i,j}^{next\ step} = w_{i,j} + \eta\left(y_j - y'_j\right)x_i$$

where η is the learning rate, y_j is the desired output and y'_j is the actual output. This equation is known as the perceptron learning rule. The perceptron learning rule closely resembles the convergence rule for stochastic gradient descent.

Figure 7. Perceptron/linear threshold unit



An Artificial Neural Network (ANN) has (generally) several layers, where the first layer is called the input layer and the last is called the output layer. The layers in between are called the HIDDEN LAYERS. Usually, an ANN with 2 or more hidden layers classifies as a DEEP ANN and correspondingly, the training is called DEEP LEARNING. A NN with 2 hidden layers is called 2 Layer Deep Network and likewise for other depths. ANNs form the core of Deep Learning. ANN can handle large and complex problems such as classifying billions of images, speech recognition services, recommending the best songs/ videos to listen to, and watching or learning to beat the world champion in the game of Chess.

Training a Neural Network simply refers to finding out the weights of the interconnection of neurons inside the network. In a network consisting of a large number of input layers with thousands of neurons at each layer with hundreds of thousands of connections, the task is difficult and needs to be done systematically.

A neural network can solve the complex problem as it uses several hyperparameters. This makes the neural networks both flexible and complex to design. There are several design parameters to set, including the number of layers and the number of neurons per layer. Also, the activation function at each layer and the bias are to be defined. Additionally, the weights of interconnections have to be derived, starting from the random restart and using the backpropagation technique. We will see shortly that there are standard API in Keras and Tensorflow through which this process can be customized within a feasible range.

An optimal number of hidden layers is an important parameter to select in a neural network. Although, some researchers have proved it theoretically that a single hidden layer is capable to provided competitive results for any complex problem, given that it is having a sufficient number of neurons. However, suitably choosing the number of hidden layers can greatly reduce the required number of neurons and gives the designer, the scope to model the network with much greater flexibility and with the reuse of already optimized layers. Also, the hierarchical architecture efficiently facilitates the implementation of the backpropagation algorithm. One should wisely increase the number of input layers until the model starts overfitting, which is not desired.

Lastly, one important parameter of consideration is the activation function. In most cases, the Rectified Linear Unit (ReLU) is a good choice. This is because the derivative of ReLU is the most suitable curve for the optimization of weight values through the gradient method.

For most complex tasks, there is a requirement for hundreds of layers, but not all are fully connected. Additionally, the requirement for training data also increases with the number of parameters/ hidden layers (Stergiou et al., 2021). Fortunately, for most complex real-life problems, it is not required to train the neural network model from scratch. Rather we can use pre-trained neural network models or use TRANSFER LEARNING to freeze some of the layers of the pre-trained models and directly use them in our custom models.

Also, the number of neurons in each layer is a tricky issue to handle. Usually, the number of input neurons is related to the type of input object. For example, in the case of image recognition, if the input image is greyscaled and of size 50X50 pixels, then, a network can be designed with 2500 neurons at the input layer, to read each of the pixel values in the image. Usually, a FUNNEL ARCHITECTURE is implemented, where, there is a decreasing number of neurons as we move from the input layer toward the output layers.

The fully connected internal layers of a neural network are called the penultimate layers. The methodology of transfer learning is clear from the above example. The objective is straightforward, as indicated in Figure 8. One can use a pre-trained model for designing any specific new related model. It is the same approach we discussed in section 4 for the design of an automated system for litter detection and classification. A pre-trained model of CNN is presented which is having an accuracy of 75 percent over ImageNet, in Top-1 Classification categories. We discuss the architecture of the same pre-trained CNN. Furthermore, we describe a transfer learning approach for using the frozen internal layers of the pre-trained model for a high-performance custom model.

Figure 8. Illustration of a deep neural network with two hidden layers

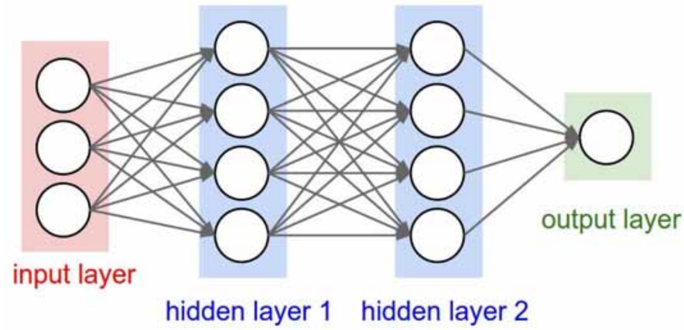


Figure 9. Transfer learning (Tan, 2018) illustration: Network A is a trained network over a dataset. Network B is another network that uses A's both penultimate layers for transfer learning for fine-tuning the model.

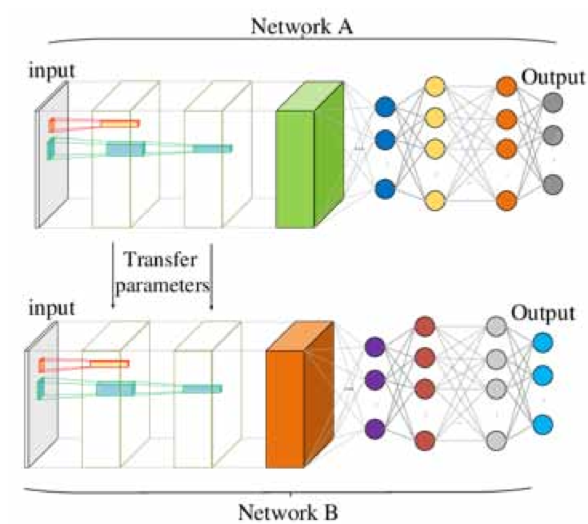
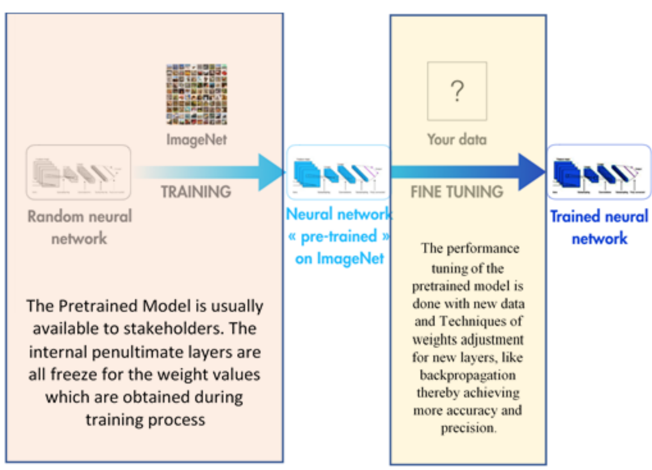


Figure 10. Transfer learning over ImageNet



CONVOLUTION NEURAL NETWORK FOR IMAGE RECOGNITION

A convolution neural network is inspired by Human Vision. These are widely used for image recognition, object identification, and computer vision in a broad perspective. It is modeled using an input layer, with as many neurons as the number of pixels in the color image, if the image is greyscaled, or three times the size of the input image if we target it for recognizing color images, considering all the three; RED, GREEN and BLUE color values of the pixels. The input layer is followed by a convolution layer with an activation function, a max pooling layer, and several repetitions of the same, depending upon the complexity, as indicated in Figure 11.

A CNN MODEL FOR LITTER CLASSIFICATION

The term litter stands for Municipal Solid Waste (MSW). A model of CNN can be implemented for the classification of MSW into its proper class so that Bio-degradable and Non-biodegradable waste can be classified and then fed to the pipelines meant for suitable disposal operations for each category (Li et al., 2019; Memos et al., 2018). We consider 34 categories of solid waste as indicated in Figure 12.

Figure 11. Image recognition using CNN: Basic architecture illustration

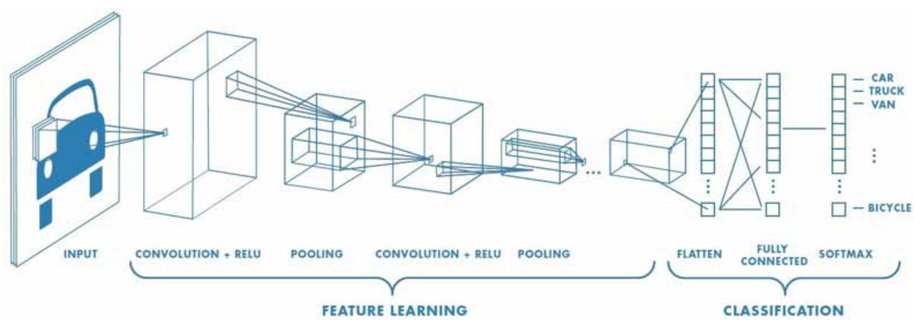


Figure 12. Litter objects (34 classes) are to be identified using the CNN model

To the best of our knowledge, this is the most expanded dataset class that is considered in any MSW category. The training dataset for these images can be imported through Kaggle (Proença & Simões, 2020). Several pre-trained models for image classification exists which can be used directly with 3-4 lines of code and can be targeted for execution over a commodity computer.

Figure 13 shows the state-of-the-art models in image classification which can be used in a pre-trained manner by direct importing the model along with weights.It is important to note that ImageNet is a Google Image repository, having billions of images, classified in 1000 classes, all nouns. Out of these 1000 classes, 34 classes are investigated which belong to the class of MSW as shown above. The transfer of learning over the pre-trained model can be implemented as shown in Figure 14.

Figure 13. High-performance CNN models, pre-trained over ImageNet and ready to use

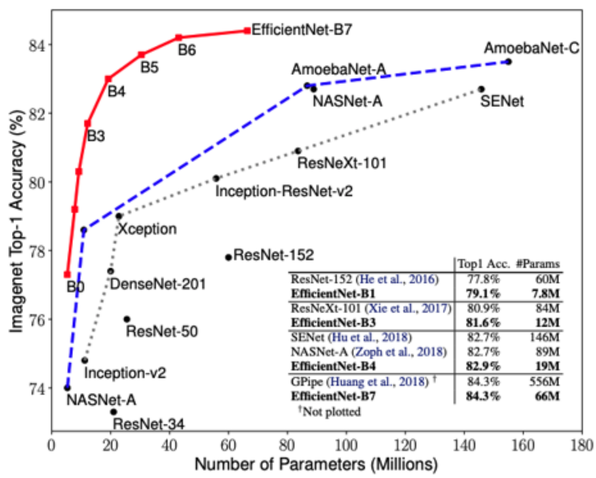
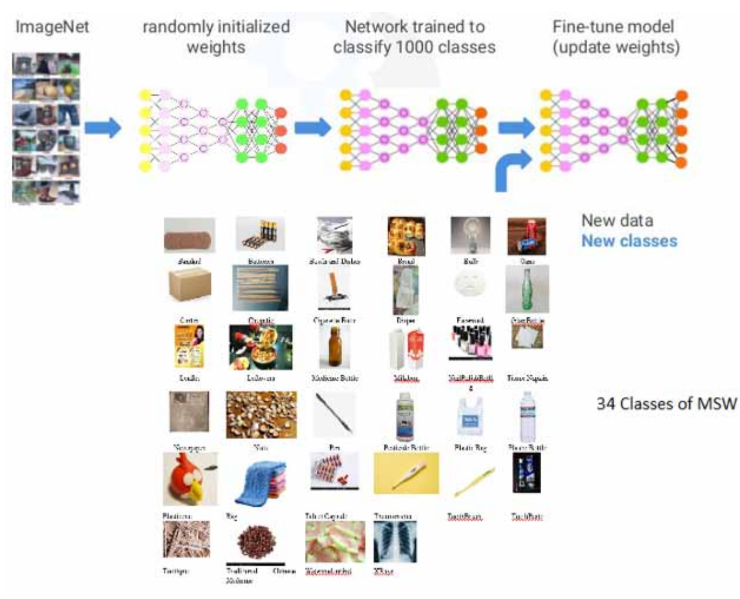


Figure 14 Implementing transfer learning to optimize the classification accuracy of 34 MSW classes of litter



SIMULATION MODEL OVER PYTHON, USING JUPYTER NOTEBOOK

Pretrained Efficient Models (Firmanyah, Supangkat, Arman, & Adhitya, 2017) can be directly used for image recognition. The following lines of code in python directly deploy a pre-trained EfficientNet-B0 Model, ready for classification.

```
######## Python Code for EfficientNet-B0 #########
######## Python Version 3.8 ##################
from tensorflow.keras.applications import EfficientNetB0
model = EfficientNetB0(weights='imagenet')
import cv2
import numpy as np
from matplotlib.pyplot import imread
from matplotlib.pyplot import imshow
from tensorflow.keras.preprocessing import image
from tensorflow.keras.applications.imagenet_utils import decode_predictions
from keras.applications.imagenet_utils import preprocess_input
test_img_path = 'waste_images/test/handwash/IMG20220314153106.jpg'
img = cv2.imread(test_img_path)
img = cv2.resize(img, (224,224))
x = np.expand_dims(img, axis=0)
x= preprocess_input(x)
print('Input Image Shape', x.shape)
my_image = imread(test_img_path)
imshow(my_image)
preds = model.predict(x)
print('Predicted Class:', preds)  # Probabilities for being in
each of the 1000 classes
decode_predictions(preds, top=5)
```

Input Image

See Figure 15.

Figure 15. Liquid handwash

Output

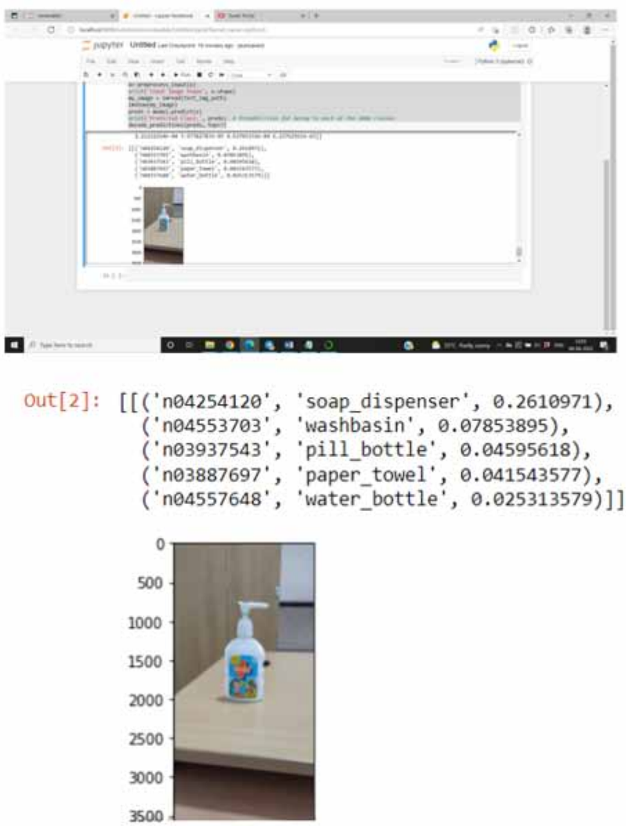
See Figure 16.

It turns out that Efficient-Net CNN models provide the best accuracy, of the order of 84 percent which is highly effective in the development of systems for municipal waste classification. The Top-1 class predicted by EfficientNet B0 is the soap dispenser which is the exact class of the MSW item. Thus, such accuracy is available with a commodity computer and with a low-resolution camera. Transfer learning methods can further improve the efficiency to a large extent, concerning the specific litter categories which pertain to that region. For example, in the towns near coastal areas of Andhra Pradesh, Coconut shells are commonly found as litter. A CNN model can be designed to implement transfer learning over EfficientNet-B0- B7 to classify it accurately in its specific class.

CONCLUSION AND FUTURE SCOPE

A model for automatic classification of municipal solid waste into specified categories can be implemented using Convolutional Neural Networks. In this paper, we indicated how such a model can be implemented using Fine Tuning of Pretrained Neural Network Model with new datasets related to litter classification. Using such a design methodology, both the software and hardware can be developed using low-cost resources and can be deployed at a large scale as it is the issue associated with healthy living provisions across cities. Several such models are in their phase of final testing and ready for deployment. We shall soon be acquainted with automatic driverless vehicles, mounted

Figure 16. Output



with robotic arms, for automatic localization and classification of the litter as per its suitable category. The most important aspects for the development of such systems are to use pre-trained models and to utilize transfer learning for fine-tuning a pre-trained model for a specific task.

This is particularly important in the modern scenario as the significant carbon emission while training a sizable model. Instead, one can use a pre-trained model and then use transfer learning to fine-tune as per the specific requirement. The same approach is proposed in this paper, wherein, an EfficientNet model, which is already trained over 1.5 million images of ImageNet, related to 1000 category labels is used as the base model and then the fine-tuning is performed on area-specific images. However, the major challenge associated with this approach is that while copying the weights from the base model, the new model also captures the bias. In the case of ImageNet, most of the images are from Europe, and thus the model works efficiently over such images, but slightly less efficient for images from other countries.

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