Deep Learning Applications in Solid Waste Management: A Deep Literature Review

Sana Shahab[1], Mohd Anjum[2], M. Sarosh Umar[3]
Department of Business Administration, College of Business Administration[1]
Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia[1]
Department of Computer Engineering, Aligarh Muslim University, Aligarh, India[2, 3]

Abstract—**Solid waste management (SWM) has recently received more attention, especially in developing countries, for smart and sustainable development. SWM system encompasses various interconnected processes which contain numerous complex operations. Recently, deep learning (DL) has attained momentum in providing alternative computational techniques to determine the solution of various SWM problems. Researchers have focused on this domain; therefore, significant research has been published, especially in the last decade. The literature shows that no study evaluates the potential of DL to solve the various SWM problems. The study performs a systematic literature review (SLR) which has complied 40 studies published between 2019 and 2021 in reputed journals and conferences. The selected research studies have implemented the various DL models and analyzed the application of DL in different SWM areas, namely waste identification and segregation and prediction of waste generation. The study has defined the systematic review protocol that comprises various criteria and a quality assessment process to select the research studies for review. The review demonstrates the comprehensive analysis of different DL models and techniques implemented in SWM. It also highlights the application domains and compares the reported performance of selected studies. Based on the reviewed work, it can be concluded that DL exhibits the plausible performance to detect and classify the different types of waste. The study also explains the deep convolutional neural network with the computational requirement and determine the research gaps with future recommendations.**

Keywords*—*Solid waste management; systematic literature review; deep learning; convolutional neural networks

I. Introduction

In recent years, waste generation around the globe has increased multi-folds due to population growth, fast urban settlement, economic development, and advancement in lifestyle [1]. The World Bank statistics indicate that the worldwide solid waste (SW) generation was approximately 2.01 billion tons per annum in 2016. It is predicted that the world will produce 2.01 and 3.40 billion tons annually by 2030 and 2050 [2]. The statistics indicate the significant increase in the SW generation around the globe [3]. More than 33 per cent of the total generated MSW are not handled in an environmentally safer manner, with the waste dumped illegally on roadsides or abandoned lands [2]. This poorly handled and openly dumped waste directly affects the environment, constitutes health risks of inhabitants, and engenders water and air pollution and land deterioration [4]. Therefore, this massive quantity of SW has become a significant threat to the ecosystem of the city and surrounding areas [5]. It has also given birth to illegal dumping [6]. It also substantially obstructs the sustainable growth of the city/region [7]. Nowadays, countries are more serious about a healthier and more sustainable environment. Several studies evidence that the leading causes of poor SWM are inadequate planning and improper operations [8], [9]. SWM bodies lack funds, infrastructure, and advanced technology in most developing countries. After the emergence of smart cities and sustainable urban development, researchers have put a lot of effort into transforming the SWM industry using current technologies and intelligent systems [10]. SW is a natural product from daily life activities and per capita waste generation significantly more in urban regions than rural areas due to high income and urban lifestyle [11]. SWM has emerged as a crucial environmental issue around the globe, especially in developing countries [12], [13]. Therefore, it is strongly demanded to create an effective SWM system for conserving resources protecting environmental and public health [14]. The environ=mental problems of SWM are very complex to resolve because of their heterogeneous nature [15].

The background analysis concludes that the SWM has focused on utilizing cutting-edge technologies to improve and automate the services. Advanced technologies such as the internet of things (IoT), information technology, machine learning (ML) have drastically improved the efficiency of various SWM processes, namely waste forecasting, collection, transportation, sorting and recycling [16], [17]. DL subset of ML methods has been significantly implemented in diverse areas of the environment, such as pollution control, wastewater, SWM services [18]. The SWM system encompasses various interconnected processes which contain numerous complex operations. This system also involves many non-linear parameters, including highly inconstant influencing factors, namely socioeconomic and demographic [19]. It is challenging to optimize the performance of these systems without affecting the health of inhabitants and the environment [20]. Therefore, DL techniques are supposed to involve in all stages of the SWM system. In earlier review studies, Ye et al. (2020) has thoroughly analyzed the 85 papers published in 2004 - 2019 and demonstrated the different applications of artificial intelligence (AI) models in the SWM service framework. In [21], the author has reviewed approximately 200 studies published during the last two decades and summarized the applications of ML methods in different stages of SWM from waste inception to final disposal. In parallel with these extensive studies, this SLR study primarily concentrates on the applications of DL models in SWM services and interpret it in view of overall process of SWM.

The main goal of this SLR study is to motivate the researchers more to apply DL techniques for solving various SWM problems involving waste detection, classification, prediction etc. It compares the performance of DL models and uncovers the best models for different tasks. It also highlights some gaps in applications of DL for SWM tasks and discusses some aspects for future priority. This information will help the researchers to choose the better model for their studies. The overall benefits of DL are encouraging for its further use towards developing an innovative and sustainable SWM system.

The survey study is structured in the following sections. Section II draws the picture of applications of various DL models in SWM. Section III comprises the methodology of the SLR architecture, which involves systematic review protocol, review questions, searching process and selection criteria, screening, article quality assessment, and data extraction. Section IV explains the overview of survey findings which includes descriptive statistics of review: country of the author academic's affiliation, mainstream journals and their publishing areas, and thematic analysis: major DL models, their applications, data set used, performance evaluation and comparison with other DL/conventional method, and depicts the detail description of CNN models. Section V illustrates the concept of DL, the design of a CNN architecture and computational requirements to implement the CNN models. Section VI identifies the Research gaps and priorities, demonstrating data acquisition, data preprocessing, model selection and architecture definition, and model comparison. Section VII comprises the summary of the SLR, important observations with shortcomings and the reason for the popularity of DL in SWM. Finally, the conclusion of the SLR study is displayed in Section VIII.

II. Sketch of DL in Context of SWM

The literature demonstrates that emerging DL models can be effectively applied in the SWM field [17]. DL is a large subset of ML techniques that comprises various computational methods and algorithms that implements artificial neural networks (ANN) with feature learning. DL techniques have significantly transformed the field of computer vision and image processing. Therefore, DL has emerged as the most attention-drawing branch of ML in recent years and has gradually reached the top. The convolutional neural network (CNN) is an epoch-making category of deep neural networks with huge potential and tremendous image recognition growth with reliable outcomes. CNN can be recognized as fundamental building blocks in diverse tasks such as photo tagging, medical imaging, and self-driving cars. A typical workflow of the DL models is depicted in Fig. 1. Generally, it comprises four main steps: (1) Data collection and preparation (2) Choosing or designing model and hyperparameters (3) Training, testing, and performance evaluation (4) Tuning hyperparameters if needed and deployment. Table VII lists the DL models applied in the SWM with research objectives/goals.

They are also exhibiting significant growth in everything from security to environment and waste management. Many eminent researchers around the globe have made remarkable contributions in SWM using DL. In SWM, DL models have been extensively implemented to solve various problems such as waste identification and segregation, real-time bin level detection, and prediction of waste generation. DL models have abilities to recognize and learn features directly from the image. This distinct feature has substantially enhanced image detection and classification. The transfer learning technique is implemented using a combination of three pre-existing CNNs, namely VGG19, DenseNet169, and NASNetLarge, to classify the waste into six categories [22]. Many CNN architectures have been proposed with different layers to categorize the different types of waste, such as recyclable: metal, paper, plastic, cardboard, nonrecyclable, medical, biodegradable, inorganic, trash, etc. [23], [24].

The pre-existing CNNs, namely enhanced ResNext [25], YOLOv2 and YOLOv3 [26], ResNet-50 and Auto Encoder network with support vector machine as classifier [27], [28], MobileNet-V2 [29] and Hybrid of CNN and multilayer perceptron [30] have also been performed above type classification tasks. Waste classification is an important activity to separate different types of waste, which significantly improves the recycling efficiency of the process. Various types of CNN with different layers have also been substantially used in many tasks of SWM other than waste detection and classification. A Long Short Term Memory (LSTM) CNN has been implemented to predict the amount of waste generation [31], [32], and carbon dioxide concentration in the waste bin [33]. Additionally, a deep CNN has been designed that consider various waste generation influencing factors to forecast the per capita waste generation [34] and demolition waste for three categories reusable, recyclable, and landfill [35]. A waste bin equipped with a camera, microcontroller, and servo motor has been built to separate the different types of waste materials automatically. The hardware of the bin is controlled by custom software based on the ResNet-34 algorithm with multi-feature fusion and a new activation function [17], [36].

Moreover, different CNN models have been implemented to identify and locate the illegal dumps using street-level image data and high-resolution satellite imagery [37], [38]. Based on the analysis of selected research papers for SLR, DL models have been extensively utilized in SWM, from waste inception to final disposal. They have been implemented in SWM processes such as waste generation prediction, bin level detection, material identification, illegal dump detection and location identification, and waste classification (refer to Tables VII and VIII). This can help to develop sustainable SWM service infrastructure through efficient resource utilization. DL has significantly impacted the recycling process as it has the power to detect different types of material and items to segregate. This has made the recycling process very effective and efficient in material recovery. Fig. 2 displays the application of the DL models in different stages of the SWM processes.

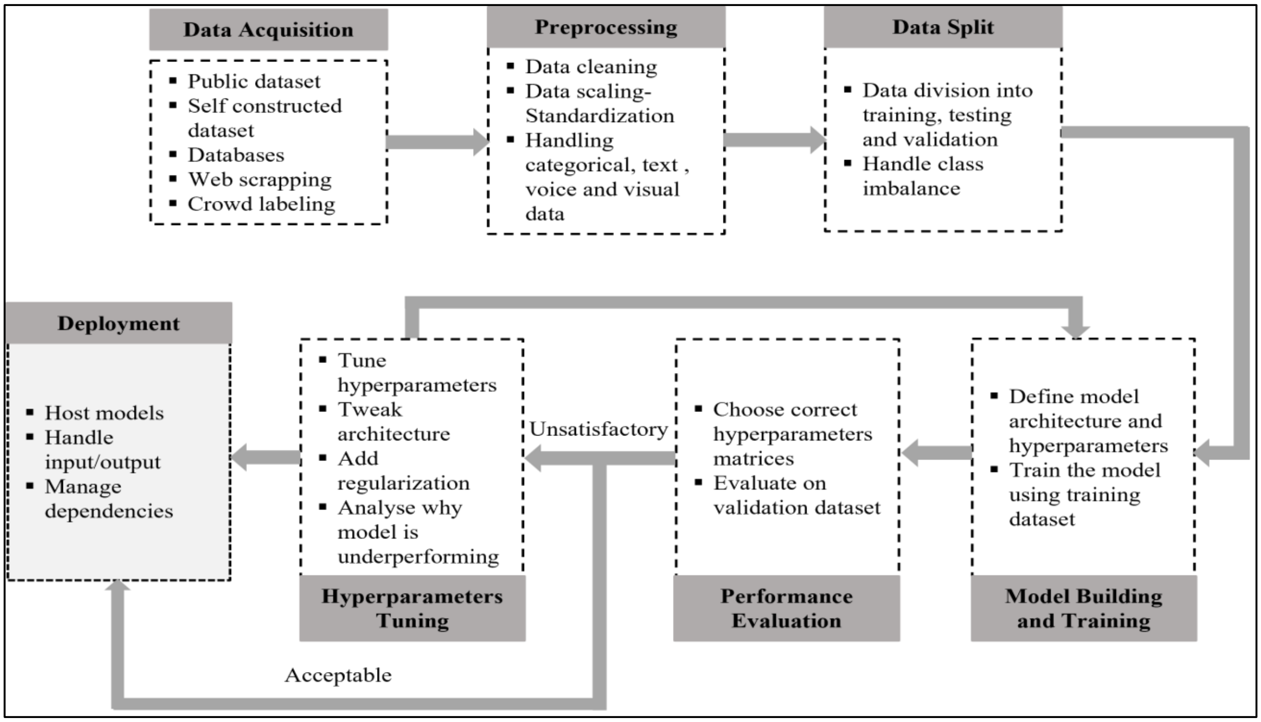

Fig. 1. Schematic Picture of DL Models Workflow.

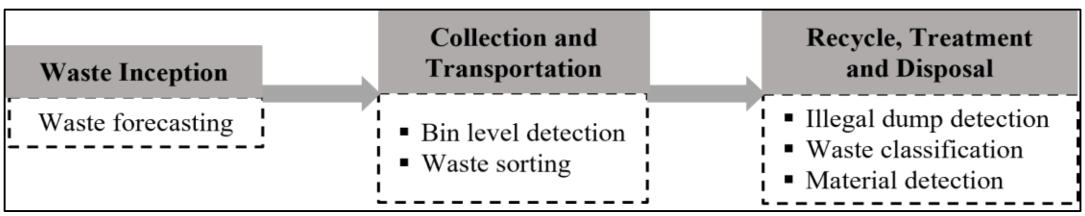

Fig. 2. Application of DL Model in SWM Processes.

To explore the potential applications of various CNNs models to provide the effective and efficient solution of different tasks involved in SWM, a thorough analysis of recently published studies is necessary to increase more advanced developments in this field. The survey demonstrates the comprehensive SLR and elaborates the various DL models implemented to enhance existing SWM techniques involved in its distinct stages, from inception to the final disposal. Some hybrid DL based approaches and performance comparison of implemented DL models with other DL/conventional models are explained to present an in-depth understanding of different models. The review study aims to provide SWM, and allied researchers are keen to apply DL approaches in their respective areas of study using major research aspects such as DL models, applications, efficiency, and accuracy. The major contribution of the survey study is to add the SLR of applications of DL in SWM, which was not previously figured out in the knowledge pool of existing literature.

III. Methodology

An SLR is carried out to examine the application of DL in SWM research published from 2019 to 2021. The SLR is defined as a systematic procedure to summarize the experimental results of the studies related to an investigation or technology, determine the gaps in current research, and develop the background for new research. The content of SLR is motivated and structured according to two systematic review studies, namely, [39], [40]. The SLR presents a comprehensible view of various DL techniques implemented in SWM. Following typical steps are conducted to enhance the creditability and reliability of the review.

A. Systematic Review Protocol

The SLR is performed to identify, evaluate, and interpret potential studies applying DL models in various SWM domains [40]. The study extensively follows the SLR methodology, which provides equitable review procedures, ensures quality to credibility, and understands results and conclusions. The SLR has a standard protocol comprising three phases: planning, execution, and reporting [40], [41]. The systematic review protocol defines the methodology of locating, studying, analyzing, and evaluating the research articles. Fig. 3 demonstrates the proposed review prototype based on the SLR guidelines. The SLR protocol describes the review process and is generally explained in technical reports.

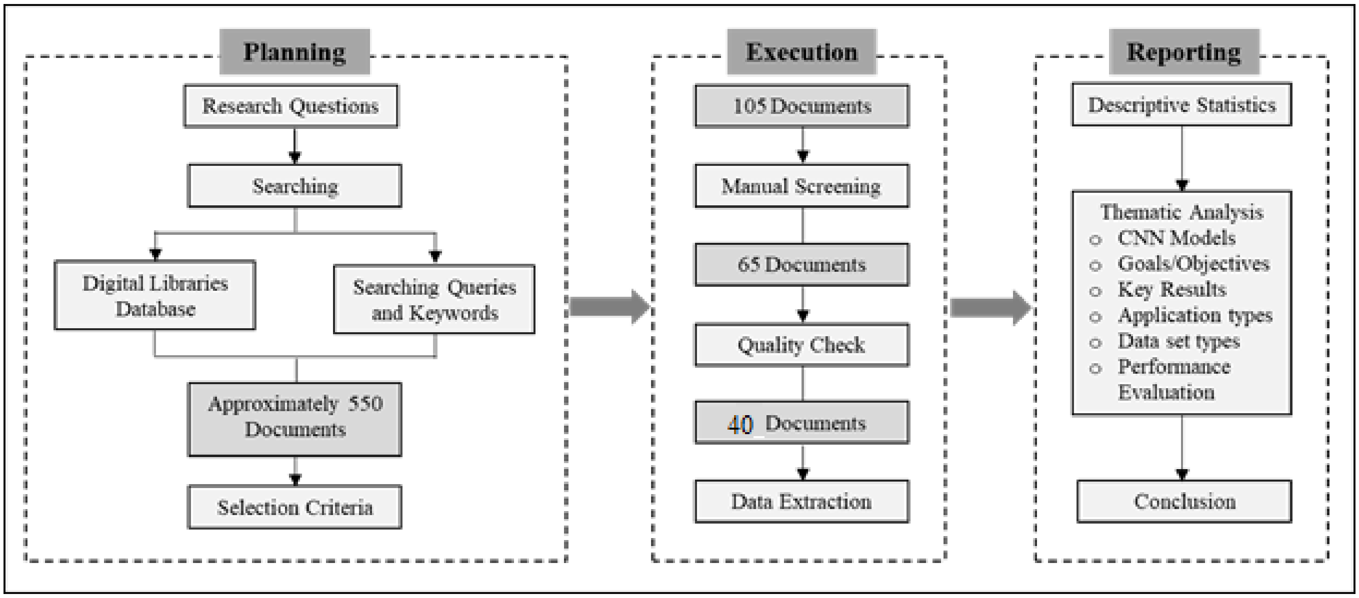

Fig. 3. Flowchart Displaying the SLR Procedure.

B. Review Questions

The primary objective of the SLR is to recognize and assess the published literature that implements the DL model in SWM. The following typical review questions are formulated and addressed to execute the proposed methodology.

RQ1: What are the different applications of the DL model in SWM?

RQ2: What are the DL models implemented to solve SWM problems?

RQ3: How is the performance of different models with respect to other algorithms and techniques?

C. Searching Process and Selection Criteria

The methodology considers an individual research paper or article as a review unit, called a document. All the documents are retrieved from a global digital libraries database, namely Scopus, Elsevier, Google Scholar, Springer, IEEE, Wiley, Emerald, and Web of Science. These are the top libraries that contain peer-reviewed global research from multiple disciplines and are widely accessed by authors to perform SLR. The preliminary search retrieved numerous articles associated with the SWM, DL and CNN but did not exhibit the direct implementation of the DL model in SWM. Additionally, many publications were also in top search, applying the conventional model (such as statistical model) in SWM. This initial search retrieved approximately 550 documents from 2019 to 2021 from the digital search libraries. Then, structured query searches with inclusion and exclusion criteria were executed to retrieve relevant literature and restrict the number of documents. These search queries included some keywords for accepting and rejecting the documents [42]. In SLR, the application of DL was the main keyword, and SWM was the context in the query string. Therefore, all searched queries were around two aspects, (a) application of DL (b) context: SWM. Table I depicts the matrix of retrieved documents for chosen keywords from afore mentioned digital libraries.

TABLE I. THE COUNT OF RELEVANT PAPERS FOR DIFFERENT SEARCH STRINGS FROM VARIOUS DIGITAL LIBRARIES

Key-word	Waste	MSW	Gar-bage	Trash	Litter	Rub-bish	Dump
CNN	149	87	17	12	3	1	2
DL	163	78	20	8	2	5	3

Additionally, the inclusion keywords were “waste management”, “garbage”, “litter”, “trash”, “dump”, “rubbish”, “deep learning”, “convolutional neural network”, and “deep neural network” while exclusion keywords were “waste recycling”, “wastewater treatment”, “waste-to-energy”, “sewer systems”, “waste incineration”, and “vehicle routing”. The gathered literature was analyzed and evaluated in a methodology context covering the studies that implemented the DL techniques to address the SWM issues. After executing the search as mentioned above procedure, 105 studies were uncovered as pertinent to the search topic for 2019-2021.

D. Screening

Manual scrutiny was carried out to ensure the completeness, reliability, and quality of SLR. Inclusion and exclusion criteria were set to make the scrutiny process straightforward, manageable, and objective. Table II displays the chosen inclusion and exclusion criteria to select the papers under four categories for further review. These categories were publication type, document language, accessibility, and subject/title. Then, all selected documents in the searching and data collection process were reviewed according to the attributes set in Table II. The journal or conference research was selected in the first screening, completely accessible and available in English. Generally, conference papers lack quality; therefore, their use in SLRs is uncommon [43]. But few good qualities conference papers were considered in the study. Moreover, their title / subject was also analyzed to determine and choose the most competent research.

TABLE II. ATTRIBUTES, INCLUSION AND EXCLUSION CRITERIA USED TO SELECT THE RELEVANT STUDIES FOR ANALYSIS OF SLR

Attribute	**Inclusion criteria**	**Exclusion criteria**
Publication type	Journal articles and conference papers	Book chapters, Patents, Magazines articles, Conference posters, Thesis, Editorials, Industry and Market reports etc.
Document Language	English	Other than English such as Chines, Spanish, Russian etc.
Accessibility	Full text of document accessible	Abstract, partially accessible, or inaccessible
Title/Subject	The main topic was solid waste management. The research applied pre-trained or designed CNN model	The main topic was related to any technology or a specific area such as the IoT, AI, and ML. The research applied any ANN other than deep neural networks.

Additionally, the abstract and conclusion were also rigorously inspected and analyzed in the context of the search topic to determine the more suitable papers and eliminate the duplicate documents having different titles but identical content. It was also investigated that the selected documents were concentrated on applying DL models in the context of SWM. After accomplishing the entire screening process, 65 studies out of 105 were promoted for further process.

E. Quality Assessment

After conducting the screening process, a quality check was performed for all selected studies. The quality assessment checklist was formulated to assess individual research and prune the insignificant and irrelevant research [40]. Ten quality criteria were determined to develop the checklist, and each study was evaluated qualitatively. A questionnaire was formulated to represent the criteria in the form of questions answered on the Likert scale of 5. The Likert scale and designed questions are presented in Table III and Table IV. The overall score of each paper was calculated by adding the points achieved in all questions stated in Table IV. The article was chosen for review if it had an overall score of more than or equal to 25 points. The top 40 papers out of 105 were picked after performing the quality assessment process.

F. Data Extraction

The pertinent data is extracted from all selected studies and summarized in Tables VI and VII to determine the consolidated outcomes. This extracted data includes the items, namely implemented DL model/technique, study goal/objective, key findings, application domains, dataset utilized in model evaluation, and performance comparison with other benchmark studies.

TABLE III. LIKERT SCALE TO EVALUATE QUALITY ASSESSMENT QUESTIONS

Criteria fulfilled	**Completely**	**Substantially**	**Partially**	**Poor**	**Not**
Assigned Score	5	4	3	2	1

TABLE IV. QUALITY ASSESSMENT CRITERIA AND CORRESPONDING QUESTIONS TO SELECT THE HIGH-QUALITY RESEARCH STUDIES

Criteria	**Questions**
Problem definition	Q1: Examine that the problem is clearly stated and has well-defined objectives.
Credibility	Q2: Justify that the problem is well formulated and the proposed approach is practically implemented on actual and sufficient data.
Methodology	Q3: Determine the applicability of the research methods and software platform in the context of the study.
Analysis and conclusion	Q4: Investigate that the accuracy is computed and critically discussed in conclusion.
Argumentation	Q5: Determine those results are compared them with other benchmark studies.
Scope	Q6: Confirm that the application area and scope of research are figured out.
Significance	Q7: Validate that the research has a remarkable contribution to the knowledge pool and/or enhanced the technology.
Structure and writing	Q8: Verify that the study comprises smooth articulation among sections with appropriate academic writing language.
Presentation	Q9: Assess the clarity of the content in the context of research goals.
Referencing	Q10: Verify the reliability and relevance of the cited references in the context of the study.

IV. OVERVIEW OF SURVEY FINDINGS

A. Descriptive Statistics of Review

In the SLR study, 40 research studies were considered published globally in the recent three years, i.e., 2019(7), 2020(22) and 2021(11). All the studies were reviewed according to the country of the academic's affiliation to analyze the contribution of various regions in the subject area. Asia published the most significant number of studies that focused on the review subject area (57.5%), and most of these studies were performed in China (22.5%). 35 % of total studies were contributed from the European region, and 7.5% were from Australia and Africa. Researchers from developing countries conducted 60% of the total studies. At the same time, the remaining 40% belonged to the developed countries, with the categorization of developing/developed countries according to the Human Development Report [44]. The statistics exhibited that researchers from developing countries focused more on SWM than developed countries. The literature evidenced that SWM was a crucial problem in developing countries; therefore, authors gave more attention to SWM research and published more studies. Motivated by the SLR study in [45], all the selected studies were analyzed by publication to determine the mainstream journals and their publishing areas. Table V depicts the list of journals and conferences. The best journals of studies subject with documents count were IEEE Access (5) and Waste Management (5). These results concluded that electronics and computer science researchers focused on applying the current state of the art of their field and invested more effort to solve the SWM issues by developing automatic and intelligent systems. Additionally, Waste Management was dedicated to SW Management, Disposal, Policy, Education, Economic and Environmental assessment. According to the analysis of publishing areas of each journal, it was deduced that SWM research was strongly related to the environmental sciences.

B. Thematic Analysis of Review

After the emergence of the various computational model of DL, no review study consolidated the applications of DL models in SWM and allied fields. The analysis of compiled studies unveiled four major applications of DL in SWM, namely waste detection, identification, bin level detection, and forecasting of waste generation. Additionally, DL was also applied to perform tasks such as demolish material prediction, custom software development for robot control, defect detection in potatoes, and different types of polythene material.

Table VI displays the applications of DL models identified in considered studies and implemented model performance evaluation for the used data set. All the studies except one had applied the proposed model on an actual data set which showed the experimental performance of the models. Only one study had performed the experiments on simulated data to evaluate the model performance. A significant number of studies had compared the performance of the implemented model with other DL/conventional models. Moreover, most studies had a sufficiently large data set to train, validate and test the proposed model. Therefore, it could be concluded that the performance of the models was reliable and could be utilized for comparison in further studies.

TABLE V. THE LIST OF PAPERS CHOSEN FOR THIS SLR ACCORDING TO JOURNALS / CONFERENCES WITH THEIR PUBLICATION AREAS

Publisher	Journal/Conference	Focused Areas
Elsevier (13)	Automation in Construction (1)	Computer-aided design and engineering, Product modelling and process simulation, Automated inspection, and robotics
	Case Studies in Chemical and Environmental Engineering (1)	Environmental and chemical engineering applications- Water, Air, soil, waste, resource recovery, energy
	Journal of Cleaner Production (2)	Cleaner Production, environmental, and sustainability
	Journal of KSU – Computer and Information Sciences (1)	Computer science and applications, Information science
	Journal of the International Measurement Confederation (1)	Sensors, Data processing, Fusion algorithms, Mathematical modelling, processes, and algorithms
	Resources, Conservation & Recycling (1)	Sustainable production, consumption and management, Resources conservation and recycling
	Waste Management (5)	SWM generation, collection, transportation, segregation, recycling, composition, policy, environment assessment
Hindawi (2)	Applied Computational Intelligence & Soft Computing(1)	AI, Fuzzy and soft computing, Operations research, Mathematical modelling, and programming
	Computational Intelligence and Neuroscience (1)	AI, Fuzzy system, Neural network, Neuro-biologically inspired evolutionary designs, Genetic algorithm
IEEE (6)	IEEE Access (5)	Multidisciplinary from science and engineering
	IEEE Transactions on Consumer Electronics (1)	Concept, design, development, production of electronics, systems, software, and services for the consumer market
MDPI (9)	Applied Sciences (2)	Engineering, environmental, earth, material, and pure science
	Applied System Innovation (1)	Computer and human-machine interaction, Applications of the IoT, Smart and intelligent system
	Electronics (1)	AI, Computer science and engineering, Systems and control engineering, control and system
	Energies (1)	Energy and environment, sustainable energy, AI systems design and control, Smart cities
	Future Internet (1)	IoT, Smart Cities and urban development, human-computer interaction, and usability
	International Journal of Environmental Research and Public Health (1)	Environmental science and engineering, Digital health, Environmental health, and ecology
	Remote sensing (1)	Remote sensing applications, Image processing and pattern recognition, Data fusion and data assimilation
	Sustainability (1)	Air pollution and climate change, Water pollution and sanitation, Sustainable development
Springer (2)	International Journal of Environmental Science and Technology (1)	Environmental science and technology, Solid and hazardous waste management, Air, water, and soil pollution
	Multimedia Tools and Applications (1)	Air traffic and online control, Real-time system, Computer-aided instruction, Remote home care, Smart system
Wiley (1)	Concurrency Computation Practice and Experience (1)	AI and ML, Big data applications, algorithms, and systems, Data science
World Scientific (1)	International Journal of Software Engineering and Knowledge Engineering (1)	Application software, Knowledge management and engineering, Smart system design
Conferences (6)	Held by Elsevier (2), Springer (2), IOP Press (1), and other (1)	AI, Computer and information science, System development, environment, and material science

TABLE VI. TABULATION OF APPLICATION TYPE, DATA SET TYPE AND PERFORMANCE EVALUATION

Reference	Application type	Data set type	Performance evaluation
[22]	Identification and classification	Real (5000 images)	The combined model classification accuracy is compared with standard pre-trained models VGG19, DenseNet169, and NASNetLarge.
[25]	Identification and classification	Real (two datasets 2527 and 5904 images)	Performance is shown with respect to the ResNext model, which is applied to different datasets.
[36]	Intelligent hardware design	Real (4168 images)	ResNet-34: 98.59%, ResNet-34-A: 99.41%, ResNet-34-B: 99.95%, ResNet-34-C: 99.28% and proposed model: 99.96%.
[46]	Smart bin hardware design	Real (565 images)	The garbage level inside the bin is monitored accurately in real-time.
[16]	Electrical and electronic item recognition	Real (210 images)	R-CNN accuracy (90% - 96.7%) is compared with respect to CNN (maximum 90%).
[47]	Intelligent robot design	Real (47000 images)	The robot picked garbage efficiently, and no comparison is shown.
[35]	Material prediction	Real (2280 demolition)	No comparison is shown.
[26]	Real-time detection	Real (375 images)	Manual verification is performed for test images.
[23]	Identification and classification	Real (2527 image)	Accuracies of CNN with various fusions are compared with AlexNet, GoogleNet, VGGNet, and ResNet-101.
[17]	Smart bin design and waste sorting	GITHUB 2020 dataset	There are shown the comparison of existing CNN models ResNet-34, VGG16, AlexNet, and ResNet50.
[24]	Identification and classification	Real (400 images)	Statistical analysis is performed after manual verification.
[48]	Defect detection	Real (images not defined)	No comparative study is performed.
[30]	Waste sorting	Real (100 images)	Improved accuracy is shown with CNN.
[31]	Forecasting	Real (weekly observation of 1000 households, 2011-2018)	Displayed 85% improved results with respect to the traditional ARIMA model.
[49]	Waste segregation	Real (2527 images)	Compared with various CNN models.
[28]	Identification and classification	Real (25077 images)	Compared with other current states of the art studies.
[50]	Garbage detection	Real (4795 and 12346 images)	No comparison, different classes accuracies are compared.
[51]	Garbage detection	Real (8000 images)	No comparison is shown, but the prediction is manually verified.
[52]	Polythene type identification	Simulated (33000 images per class)	Performance is compared with 23 layers networks with different image sizes.
[32]	Forecasting	Real (730 data samples)	Compared with ARIMA and conventional ANN.
[33]	Prediction	Real (9358 data points)	No comparative analysis is shown.
[34]	Prediction	Real (2827 data point)	No comparison with other studies is shown.
[53]	Waste classification	Real (7724 images)	YOLOv3 results are compared with YOLOv3-tiny.
[27]	Waste classification	Real (1989 images)	No comparative analysis is presented.
[29]	Waste classification	Real (2527 images)	Performance is compared with MobileNet, InceptionV4, InceptionResnetV2, Xception, DenseNet121 & 169.
[17]	Waste classification	Real (4163 images)	Performance comparison is shown among four models DenseNet169, ResNet50, VGG16, and AlexNet.
[54]	Localization and recognition	Real (56,964 images)	Performance is compared with BNInception and ResNet-50.
[55]	Real-time waste identification	Real (2527 images)	Various models based on MobileNetV2, InceptionV2, & V4 are tested to obtain optimal accuracy.
[56]	Construction and demolition waste classification	Real (Two data sets of 525 and1758 images)	No comparison with other studies is shown.
[57]	Waste classification	Real (More than 25000 images)	The performance of VGC19 is compared with ResNet50 and InceptionV3.
[58]	Glass and metal detection	Real (2000 images)	Performance comparison analysis of three models is shown.
[59]	Classification	Real (6640 images)	Accuracies of Resnet101, EfficientNet-B0, B1 and ensemble are compared to determine the optimal model.
[60]	Classification	Real (500 images)	No comparison with other studies is shown.
[61]	Detection and classification	Real (369 images)	No comparison with other studies is shown.
[62]	Detection and recognition	Real (546 images)	No comparison with other studies is shown.
[63]	Waste dump detection	Real (5000 images captured by UAV)	No comparison with other studies is shown.
[64]	Plastic classification	Real (109820 images)	Proposed CNN accuracy is compared with AlexNet, MobileNet v.1 and MobileNet v.2
[65]	Waste classification	Real (2527 images)	Multilayer hybrid CNN accuracy is compared with AlexNet, ResNet50, and Vgg16.
[38]	Illegal dump detection	Real (3000 images)	No comparison with other studies is shown.
[66]	Classification	Real (5416 images)	Various state-of-arts models are compared.

TABLE VII. TABULATION OF DL MODELS, OBJECTIVES AND KEY RESULTS

Reference	DL Model/Technique	Goal/Objective	Key results
[22]	Transfer learning: proposed a combination of pre-trained models VGG19, DenseNet169, and NASNetLarge	Waste classification into six categories	Classification accuracy: more than 92% for all distinct classes with an average of 96.5%
[25]	DNN-TC: an improved version of ResNext	Waste classification into organic, inorganic, and medical waste	Applied on two data sets and obtained accuracies 94% and 98%, respectively
[36]	ResNet-34 incorporating input images with multi features, reuse of the residual unit and a new activation function	Developed hardware of automatic garbage classification system	Identified 14 subcategories of recyclable and nonrecyclable with an accuracy of 99.96%
[46]	IoT and Tensor flow	Smart bin with real-time waste object detection and classification features	Obtained hardware of automated segregation and monitoring system
[16]	CNN and faster region CNN	E-waste recognition and classification	Acquired e-waste equipment identification accuracy between 90% - 96.7%
[47]	SegNet and ResNet	Robot for waste picking from grass	Attained waste recognition accuracy up to 95% without path planning
[35]	Deep neural network	Prediction of demolition waste for reusable, recyclable, and landfill	Prediction accuracy recyclable: 95%, reusable: 98%, and landfill: 99%
[26]	YOLOv2 and YOLOv3 CNN	Garbage container detection and classification	Identified and classified the garbage and its type with an accuracy of more than 90%
[23]	DL models using the feature and score-level fusion	Waste categorization into five classes	Obtained accuracies 94.11% and 94.58% for double fusion PSO and GA, respectively
[17]	Integration of IoT and ResNet-34, VGG16, AlexNet, and ResNet50	Sorting of digestible and non-digestible along with smart trash bin	Exhibited maximum accuracy of 95.31% and successfully real-time bin monitoring
[24]	Two Deep CNN with four and five layers	Waste classification into four categories	Computed accuracies of four and five layers DCNN 61.67% and 70%, respectively
[48]	CNN with nine layers	Real-time defect detection into potato	Achieved 83.3% accuracy in real-time
[30]	Hybrid of CNN and multilayer perceptron	Waste sorting as recyclable and others	Determined the accuracy more than 90%
[31]	Multi-site LSTM CNN	Waste forecasting	Reported RMSE, MAE and MAPE as 0.5, 0.41 and 0.74
[49]	DenseNet121 optimized by genetic algorithm	Recyclable waste segregation	Highest accuracy demonstrated 99.6%
[28]	Auto Encoder network, CNN, Ridge Regression and Support vector machine as a classifier	Waste Classification	Achieved 99.6% accuracy
[50]	Fast region CNN	Street litter detection and classification	Achieved accuracies between 73.4% and 97.3% for different classes
[51]	Fast region CNN with edge computing	Garbage detection for street cleanliness assessment	Achieved accuracies between 81% and 93% for different classes
[52]	CNN with fifteen layers	Polythene Classification	Input image size 120x120 pixels, report accuracy for 15 layers network 99.2%
[32]	LSTM CNN	Waste forecasting	Reported R2 and MAPE as 0.96, 6, and 63.66 (Training), 0.92 and 114.05 (Testing)
[33]	Simple and modified LSTM CNN	Prediction of carbon mono oxide concentration inside the bin	Prediction accuracies exhibited by simple and modified models were 88% and 90%
[34]	CNN with three hidden layers of eighty neurons	Per capita waste generation prediction	Forecasted accuracy 94.6%
[53]	YOLOv3 and YOLOv3-tiny	Waste segregation for disposal and recycling	Mean average precision of implemented network is 94.99%
[27]	ResNet-50 and Support Vector Machine	Waste categorization into four classes	Obtained the classification accuracy of approximately 87%
[29]	MobileNet-V2	Waste categorization into six classes	The accuracy of the implemented network is 96.57%
[17]	DenseNet169, ResNet50, VGG16, and AlexNet	Waste categorization into six classes	Accuracies of all four models are 94.9%, 93.4%, 91.7%, and 89.3% respectively
[54]	Multi-task learning architecture-based CNN	Simultaneous waste localization and recognition	Shown F1 score 95.12% to 95.88%, with a 95% confidence interval
[55]	Single Shot Detector and Faster R-CNN based on MobileNetV2 and Inception-ResNet	Identification of six types of waste	Reported the accuracy for both models 97.63% and 95.76%, respectively
[56]	Two Deep CNN with multiple layers	Construction and demolition waste classification	Single and multi-waste classification accuracies are obtained 91.88% and 96.17%, respectively
[57]	VCG-19, ResNet50, and InceptionV3	Waste categorization into fifty classes	Obtained the accuracy 86.19% for fifty classes
[58]	Three CNN with different number of layers	Metal and glass detection into a waste bag	Determined the maximum accuracy for metal and glass 100% and 96.28, respectively
[59]	Resnet101, EfficientNet-B0, EfficientNet-B1 and ensemble	Waste categorization into seven classes	Overall accuracies 92.43%, 91.53%, 90.02%, and 94.11%
[60]	Faster Region CNN	Biodegradable and non-degradable waste segregation	Computed average accuracy 84.34%
[61]	RetinaNet	Waste pollutant detection and classification inside water	Obtained average precision 0.8148

[62]	YOLOv2	Classifying battery-containing devices, detecting batteries, and recognizing battery-structures	100% is demonstrated for classifying battery-containing from non-battery-containing devices
[63]	Deep CNN using Single Shot Detector	Waste dump identification on the riverbank	Masks generated on waste by the model are compared with the original image.
[64]	CNN with twenty-three layers	Different types of plastic material detection	Demonstrated the average accuracy of 74%
[65]	Multilayer hybrid CNN model	Waste classification into six categories	Shown classification accuracy up to 92.6%
[38]	Combination of ResNet50 and Feature Pyramid Network	Waste dump identification and classification	Achieved classification precision 94.5%
[66]	Seven state-of-the-art CNNs like MobileNetV3, AlexNet, ResNet	Waste classification into nine categories	Obtained accuracy from 91.9% to 94.6%

Table VII demonstrates the proposed DL models, objectives, and key results of compiled studies. A significant number of studies had implemented pre-existing CNN for self-constructed data set. In contrast, the remaining studies had designed their own CNN and applied it to their data set to demonstrate the experimental results. The deeper analysis of compiled studies deduced that most studies concentrated on the different waste identification and classification types. At the same time, some focused on the prediction of waste generation with various influencing factors. Few studies developed the smart bin using the IoT, and the DL model was used to build the custom software to control the bin hardware. One study constructed the waste picking robot from the grass ground, using DL-based custom software to manage the robot hardware. Moreover, objectives such as detecting different types of polythene materials and defects in potatoes were also obtained successfully. The key results of complied studies are discussed in detection precision and classification accuracy. The evaluation of results exhibits that the reported accuracies were more than 90%.

The comprehensive analysis of considered studies indicates that a significant number of studies had implemented pre-existing CNNs such as AlexNet, MobileNet-v2, YOLOv3, ResNet-50, NASNetLarge while remaining studies applied manually constructed CNNs which are built through a different number of neural layers. Pre-existing CNNs are developed by various researchers from academic and industry backgrounds. The CNNs have already demonstrated remarkable performance on image recognition benchmarks. These networks are trained, so only top layers, called fully connected layers, are retrained and fine-tuned according to the data set. Conceptually, these networks reutilize the weights and structure of a prior model from the convolutional layers. The construction and training of a CNN based new image recognition from scratch involve a lot of time and computational power. Therefore, the utilization of pre-existing networks increases computational efficiency.

V. Deep Learning

In the last decade, AI has completely transformed and shifted into the era of computation, and DL is the only reason for this cutting-edge development. It has a very interesting and unique feature to 'self-learn' distinctive patterns directly from the data. It has the ability to extract features automatically without hand crafting them. It has emerged as the most promising computing method to automate the categorization of visual and spatial data in the context of SWM. Nowadays, SWM and allied field researchers are getting huge amounts of street or city-level data from various systems such as city surveillance systems, unmanned aerial vehicles, high-resolution satellite imagery, or online platforms where many people participate in data collection [67]. However, conventional AI methods have limited capacity to analyze this huge amount of data which is a bottleneck for researchers [68]. DL computing techniques have the extensive power to overcome this condition through automatic analysis of a massive dataset.

DL theoretical concepts are not developed recently; it has been published as far back as the 1980s [69]. This approach has become more prevalent, understandable, and practically possible in the last decade due to tremendous growth in computer hardware, the development of exceptional computational tools, and the accessibility of massive preprocessed and annotated data necessary to implement this methodology [70]. The literature analysis evidence that it has been implemented in automation of complex data computation tasks, object detection and location in visual data, photo tagging, self-driving car, speech recognition etc., across a wide range of industries [70]. The authors strongly believed that this methodology could achieve similar remarkable advantages in SWM. It potentially saves a lot of time for manual data analysis; therefore, DL enables the SWM and allied researchers to concentrate on more crucial tasks and could develop improved features for large scale and real-time monitoring SWM systems [16], [17].

A subset of ML, DL consists of utilizing the data structures named 'deep ANN', interchangeably DL. It is fundamentally consecutive arrangements of non-linear functions or several layers of digital neurons. These multiple layers of neurons construct the deeper the network. These networks learn hidden patterns automatically from the input data without explicit construction of distinct features to categorize the data. This drives the AI to be widely understandable and usable to non-expert users. DL models are trained to perceive and learn these patterns by labelled inputs and corresponding outputs. After learning, the model predicts data that was never seen earlier [70]. This AI model, where labelled data is given in training of deep ANN, is termed supervised DL. Fig. 4 displays DL workflow using supervised learning through classification of e-waste items.

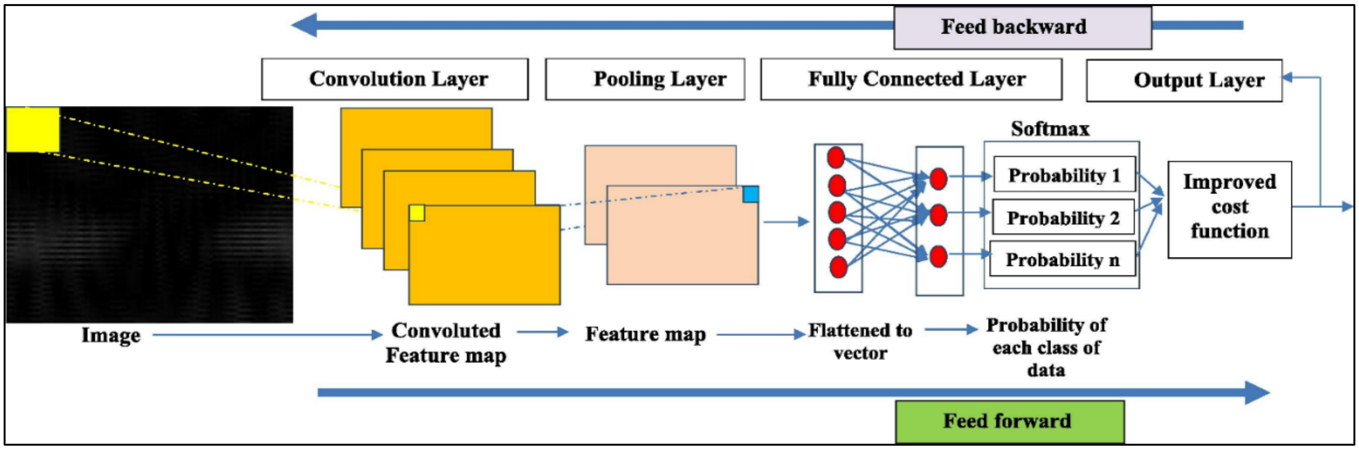

Fig. 4. A Typical Architecture of CNN.

A. Convolutional Neural Network

The CNN is an essential class of deep neural networks, more precisely, DL, a subset of ML and inherently re-branding ANN. CNN has exhibited massive growth in image recognition, so they are specially implemented to analyze visual data and perform tasks beyond classification. The CNN allows to extract the features from the image and conducts its training from these features. It is different from a conventional neural network in processing and extracting features. Image features are handcrafted to implement image recognition using a conventional neural network while CNN receives the image's raw pixels as input data, trains the proposed model, then automatically extracts the features to perform the better classification. Fig. 4 depicts the general architecture of a CNN [71]. A typical CNN has comprised an input layer, followed by the alternate combination of convolutional and pooling layer, and top of the network fully connected layer followed by classification output layer.

The input layer defines the size of the input image and holds the values of raw pixels extracted from the image. The input image dimensions are represented by the height, width, and the number of colour channels (1 and 3 for grayscale and colour images, respectively) in the image. This layer also carries out input data preprocessing such as simple rescaling or normalization, mean subtraction, normalization and principal component analysis and whitening.

The convolution layer is the core element of CNN building which comprises filter and stride. A filter is a small size two-dimensional layer of neurons mapped over a small segment of the input image and covers the whole image through shifting. The convolution operation is performed by the computing dot product between the filter and image pixel, added over the filter area. After that, the filter is shifted in the horizontal and vertical direction to perform similar computation in each area of the whole image. The step size of shifting is called stride. When the filter moves over the input image or output of the preceding layer, it uses the same set of weights to carry out the convolution operation to create the feature maps. Therefore, feature maps and filters are equal in number. All feature maps comprise a different set of weights and neurons of the same map using similar weights for different input regions. Initially, all these filters have random values and become network parameters that will be learned subsequently.

The pooling layer decreases output data size from the convolution layer, called down sampling operation. Various types of pooling functions occur, but max pooling is generally utilized. It reduces the count of connections to the following layer, the typically fully connected layer. It also decreases the count of parameters learnt in the previous layer and does not perform any learning. The max-pooling filter gives the maximum value for every sub-region.

A fully connected layer is called a hidden layer, like an ANN. It connects each neuron of the preceding layer with every neuron of the successive layer. It determines the patterns to categorize the images by incorporating the features learned in the preceding layers and usually learns the non-linear function.

B. Computational Requirements

Generally, deep CNN models are implemented in several programming languages: Python, R, MATLAB, Java, and C/C++. Many open-source software libraries such as TensorFlow, PyTorch, OpenCV, Theano and Microsoft CNTK (Cognitive Toolkit) provide a diverse range of functions for most of the programming languages, including Python and R [72][73]. Moreover, software libraries like Keras provide a highly simplified interface for the DL libraries like TensorFlow.

The physical resources required to execute DL models are either Graphical Processing Unit (GPU) or Central Processing Unit (CPU). Generally, a CPU comprises only 2 to 16 cores, which are the smallest computation unit in a computer. A GPU consists of thousands of more simplified cores than CPU cores, optimized to execute parallel arithmetic operations, and is best for executing DL models [74]. Therefore, GPU decreases the program execution time in significant orders of magnitude and makes physical implementation possible [70]. Nowadays, an alternative is available for computation, which does not need the local computer hardware resources, is called cloud computing. It provides online on-demand computing and storage resources for computation without user management. Platforms like Google Cloud Platform Microsoft Azure provide a subscription to execute DL models online at cloud.

VI. Research Gaps and Priorities

Even though DL models have been extensively implemented in recent years to solve various SWM problems, they are still in the early phase of evolution and application. This SLR study has uncovered some gaps in applying DL models to SWM, and some aspects must be prioritized in the future.

A. Data Acquisition

DL models perceive insights and uncover hidden patterns from a massive amount of data applying various techniques. Reliable and enough data are the most fundamental and core elements of DL models applications. The quality and quantity of historical waste data are extremely crucial for the reliable performance of the DL model [75]. However, most of the studies deal with small or medium datasets, which could be attributed to SWM infrastructure and practices [16], [47]. Generally, SWM associated data are collected and organized by distinct channels encompassing various stakeholders. This hybrid management structure makes the data gathering and compilation extremely hard and complex [76]. Due to the lack of SWM related data, precise DL models are tough to implement. Furthermore, authors have analyzed that most research studies have utilized self-constructed data set for training, validation, and testing purposes. Therefore, it implies that the data set for DL model implementation is not available in the public domain. The scarcity of open benchmark data set is a major obstacle in implementing DL models in SWM and allied fields.

Now-a-days, many techniques are available to construct a large data set from a smaller one. For example, data augmentation is one of the most prevalent methods in fields such as data analysis to increase data size for effective and accurate model implementation. In SWM tasks such as waste classification material detection, the data augmentation technique is utilized to increase the amount of sample data for better performance of the DL model [52], [64]. Additionally, the collection of waste generation data is growing due to extensive waste monitoring, and some constructive data set are accessible freely [77]. Currently, city monitoring data is collected using remote sensing, geographic information system, unmanned aerial vehicle photography, satellite imagery, and modern technologies like IoT, sensors, and radio frequency identification to develop the SWM monitoring system. These sources generate a massive amount of data; therefore, it is highly demanded to develop a system for combining these existing data resources and constructing a data management platform with a unified protocol for distinct formats and types. Data fusion technology can also be applied to analyze and monitor the interconnection between distinct systems, databases and data types. Furthermore, data sharing mechanisms must be flexible and open to develop the reliable and quality data opening environment.

B. Data Preprocessing

Data preprocessing is not a vital phase for the AI, ML and DL models, but it is the highly consequential phase. If the collected data are processed correctly, it significantly impacts the training phase and predicted outcomes. Generally, it decreases the training time of DL model and sometimes enhances the model performance. Besides this, it is also instrumental in transforming the collected data into an appropriate form for the subsequent model phases. Missing values and noise are common in data collection and recording. Mostly linear interpolation or mean value replacement are applied to fix missing data points [31], [78]. But these methods have one major drawback of information loss. In [79], the author applied the ANN to reconstruct the missing values in methane generation data and showed a significant decrease in mean square error. This leads to the novel direction for constructing MSW data missing value to future researchers.

In addition, the selection of suitable input variables for the DL model can extensively control the performance of the training phase and the robustness of DL models. These appropriate variables would improve the performance and reduce the modelling complexity. The SWM system is very complex contains various interconnected processes with numerous complex operations. This system also involves many non-linear parameters, including highly inconstant influencing factors, namely socioeconomic and demographic and operating control parameters [80]. The labelling of visual data is also highly consequential on supervised DL model learning performance and predicted results. An inaccurate label can significantly confuse the model learning, which will lead to erroneous results [81]. The survey analysis has uncovered that most of the existing studies have applied the DL algorithm on a selected set of labelled data that is correct in real-world applications. Furthermore, precise data labelling is cumbersome and time-consuming [81]. In [81], the author has demonstrated a DL technique to select the most appropriate data for labelling cost-effectively. This active labelling of data can focus on attaining the best training and testing performance for waste classification and illegal dump detection using the DL model with limited data. This can also be used to create the benchmark data set for different categories of waste.

C. Model Selection and Architecture Definition

Now-a-days, numerous DL models are available for implementation, but there is no specific rule to choose the best model. Generally, CNNs are applied to imagery or spatially related data, while LSTM/RNN are performed best on sequential data. Table VIII demonstrates the strengths and drawbacks of the DL models used in SWM and can help select the appropriate model. The DL model selection in SWM depends on the types of input data and tasks performed. The right accuracy selection also plays a crucial role in choosing a suitable DL model. Defining DL model architecture is a critical step for successfully executing model over studies data set with acceptable accuracy. There is no clear set of instructions to build the model, but the following two things help to develop model architecture. The model must possess satisfactory accuracy on the studies data set and must be easily retrainable or exist as a pre-trained model. The practical aspect associated with accuracy is the speed versus accuracy tradeoff. DL communities have currently constructed a diverse range of architectures for distinct use cases that can be applied in real-world problems. For example, if someone has a constraint of computing resources, then one must choose fast architecture such as MobileNetv2 [29], [55], [66], and if someone does not have the above constraint, then one can go state-of-art model which promises then best accuracy. Furthermore, some architectures are lighter and faster as they cut down the layers, making them faster and slimmer.

Additionally, different existing or pre-trained models can be applied to the same data set to obtain the best model to perform the target task. Based on Table VI and Table VII, CNNs have been widely applied in waste classification with remarkable accuracy [28]. However, these are rarely implemented in other SWM processes. Therefore, researchers have opportunities to develop new CNN architectures or can apply existing CNN in other processes. LSTM/RNN models have been implemented to forecast waste generation, but these models can have potential applications in other sequential data related to SWM [31]–[33].

TABLE VIII. STRENGTH AND DRAWBACK OF DL MODEL APPLIED IN SWM WITH THEIR APPLICATIONS

Model	Strength	Drawback	Applications in SWM
CNN	Capable of extracting features automatically; therefore, no explicit crafting of features. They have been used effectively for imagery data. Perform well with data that has spatial relationships.	Require massive sample data for training Require parameters tunning	Waste detection and classification- Glass, Metal, Trash, Cardboard, Plastic, Medical, Recyclable, Nonrecyclable, e-Waste, Polyethene, Organic, Inorganic etc. Object detection-Battery, Defects in potatoes, Waste bags etc. (refer to Table VI)
LSTM /RNN	They have been efficiently used for sequence data like text, speech etc.	Require massive computation	Waste forecasting, Gas prediction inside the bin [31]–[33]

D. Model Comparison

It must be conducted to evaluate the effectiveness and performance of the DL model. This SLR analysis has uncovered that many studies have applied on one model with showing any comparative performance with other model [27], [33], [61]–[63], [34], [35], [38], [47], [48], [50], [51], [56]. In some studies, the outcomes from different models have been compared and analyzed to choose the best one while they lack in comparison to similar models from different studies [24], [26], [31], [32]. However, these studies have shown good results, but this comparison does not provide evidence for the best model selection. Very few studies have utilized the results of other studies as a baseline for comparison, but both results are Computer using the different data set; therefore, this type of comparison does not seem very meaningful and convincing [15], [28]. In waste classification and similar tasks, a significant number of studies have demonstrated the comparison with a similar type of model on the same data set and shown better accuracy (refer to Table VI). This SLR has also undermined that the current studies do not explain more about the model description, such as hyperparameters setting and fine-tuning. Therefore, it is extremely difficult to reproduce the results from implemented DL model. Consequently, the author has suggested explaining the DL model description with minor detail that will help advance scientific research with previous outcomes and fast development and applications in SWM.

VII. DISCUSSION

The overall discussion about the SLR study can be partitioned into three subsets. The first subset describes the summary of the study. The second subset discusses an important observation with a shortcoming. The third subset explains why applications of DL models in SWM is growing with remarkable momentum.

First, the comprehensive SLR concentrates on analyzing and evaluating the various DL models and their applications in SWM, obtained from 40 research studies published in reputed journals and reliable conferences between 2019 and 2021. The reported key results of all complied studies are displayed, and performance comparisons shown within the study are also manifested. The outcomes of the SLR study indicates that various types of CNNs, manually constructed, pre-existing, and hybrid with other approaches, have been implemented to perform various tasks. Generally, waste identification and classification problems are fundamentally complex as waste have ill-defined features readable to the machine. Therefore, traditional ML and image process algorithms do not have sufficient capabilities to provide a reasonable solution in terms of effectiveness and efficiency. Other than waste classification, DL models have also been applied to predict waste generation, gas concentration and illegal waste dump detection.

Second, the in-depth analysis of the literature unveils that all the studies used self-constructed data set. Therefore, it can be confidently concluded that no benchmark data set exists, which is a major drawback for the researchers comparing their model performance with benchmark results. So, firstly it can be strongly recommended that an annotated benchmark data set be constructed for each waste category for future research. Secondly, it also seems clear that DL models provide more cutting-edge techniques in SWM, which are significantly effective and efficient compared to traditional ML and image process approaches. Therefore, DL models have gained sufficient momentum in the SWM research community to solve a wide variety of problems.

Third, the field of DL has got popular recently, so researchers from SWM research communities are increasing interest in applying DL models for SWM services. The SLR evidence that applications of DL models in SWM have started recently, especially in the last three years. The literature in this field is growing at a significant pace with novel applications in different SWM tasks. Therefore, the SLR study has focused on the research published in the last three years. The maturity of DL applications in this field can take a long time as the SWM system has highly complex interconnected components. It has been practically applied in many applications, namely intelligent waste identification and classification. For example, SpotGarbage, an Android App and robot for waste picking over grass, has successfully applied the DL models to detect, localize, and classify the waste automatically. Furthermore, most of the chosen studies for SLR are exploratory, so it can also be anticipated that more applications will be in practice soon.

VIII. Conclusion

Various AI and image processing approaches have been implemented for solving the SWM problems, such as waste generation prediction and waste level detection in the bin over the years. But in the last decade, DL has been successfully applied in diverse domains. Even though the main focus of DL (especially unsupervised learning) is in the image processing domain, this study has performed the SLR of the emerging research relating to the DL applications in the SWM. Furthermore, these approaches are popularly known to conquer the vanishing gradient problem, which was an acute limitation on the depth of ANN. In the last few years, lots of research efforts have been made to apply DL in the SWM domain. This study performs an SLR of published research that applies the DL models for SWM. Forty relevant research studies are uncovered after executing the rigorous SLR procedure. These research studies are analyzed and examined based on the SWM problem they focused, type of data set utilized, implemented models comparison, and performance evaluation according to the performance matrices used by individual papers. The performance of DL models is compared with other existing techniques. The overview of findings implies that DL exhibits better performance and outperforms as compared to other prevalent ML and image processing techniques.

Significance of this SLR: The identified DL learning techniques have been effectively applied to model the complex processes in SWM. Therefore, DL is drawing the attention of researchers from around the world and has emerged as a foundation for SWM problem-solving. This SLR study also provides evidence that DL in SWM is the most active research field. Furthermore, it is observed that DL models consist of cutting-edge techniques to solve the SWM problems. These techniques are remarkably efficient and do not need hand crafted features as traditional ML and image process approaches. Hence, DL models have obtained significant popularity in the SWM research community to solve a wide range of problems. The main goal and significance of this SLR provide the background about different DL models with their performance in a variety of SWM tasks and gaps for future research on this particular topic. It also elaborates the basic DL model (CNN architecture) design and provides comprehensive information about DL in SWM, which could be highly useful to SWM practitioners.

For future work, it is recommended to implement the general concepts and best practices of DL, as illustrated through this SLR, to problems of SWM where this cutting edge approach has not yet been significantly applied. One crucial suggestion is to construct the annotated benchmark data set for public use. It is strongly needed to compare and enhance the performance of the DL models. It will also provide a boost to the applications of models in SWM.

Acknowledgment

This research was supported by the Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2022R259), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

References

[1] C. Mukherjee, J. Denney, E. G. Mbonimpa, J. Slagley, and R. Bhowmik, “A review on municipal solid waste-to-energy trends in the USA,” Renewable and Sustainable Energy Reviews, vol. 119. Elsevier, Mar. 01, 2020, doi: 10.1016/j.rser.2019.109512.

[2] S. Kaza, L. C. Yao, P. Bhada-Tata, and F. Van Woerden, What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050, vol. 1. Washington: World Bank Publications, The World Bank Group, 1818 H Street NW, Washington, DC 20433, 2018.

[3] C. Magazzino, M. Mele, and N. Schneider, “The relationship between municipal solid waste and greenhouse gas emissions: Evidence from Switzerland,” Waste Manag., vol. 113, pp. 508–520, Jul. 2020, doi: 10.1016/j.wasman.2020.05.033.

[4] M. Triassi, R. Alfano, M. Illario, A. Nardone, O. Caporale, and P. Montuori, “Environmental pollution from illegal waste disposal and health effects: A review on the ‘triangle of death,’” Int. J. Environ. Res. Public Health, vol. 12, no. 2, pp. 1216–1236, Jan. 2015, doi: 10.3390/ijerph120201216.

[5] D. Demirbilek, A. Öztüfekçi Önal, V. Demir, G. Uslu, and H. Arslanoglu-Isık, “Characterization and pollution potential assessment of Tunceli, Turkey municipal solid waste open dumping site leachates,” Environ. Monit. Assess., vol. 185, no. 11, pp. 9435–9449, 2013, doi: 10.1007/s10661-013-3263-7.

[6] D. H. F. da Paz, K. P. V. Lafayette, M. J. de O. Holanda, M. do C. M. Sobral, and L. A. R. de C. Costa, “Assessment of environmental impact risks arising from the illegal dumping of construction waste in Brazil,” Environ. Dev. Sustain., vol. 22, no. 3, pp. 2289–2304, Mar. 2020, doi: 10.1007/s10668-018-0289-6.

[7] A. S. Nagpure, “Assessment of quantity and composition of illegal dumped municipal solid waste (MSW) in Delhi,” Resour. Conserv. Recycl., vol. 141, pp. 54–60, Feb. 2019, doi: 10.1016/j.resconrec.2018.10.012.

[8] M. A. Hannan, M. Arebey, R. A. Begum, A. Mustafa, and H. Basri, “An automated solid waste bin level detection system using Gabor wavelet filters and multilayer perception,” Resour. Conserv. Recycl., vol. 72, pp. 33–42, Mar. 2013, doi: 10.1016/j.resconrec.2012.12.002.

[9] A. Malakahmad and N. D. Khalil, “Solid waste collection system in Ipoh city Solid Waste Collection System In Ipoh City:A Review,” 2011 Int. Conf. Business, Eng. Ind. Appl., no. March, pp. 174–179, 2016, doi: 10.1109/ICBEIA.2011.5994236.

[10] M. A. Hannan, M. Arebey, R. A. Begum, and H. Basri, “Radio Frequency Identification (RFID) and communication technologies for solid waste bin and truck monitoring system,” Waste Manag., vol. 31, no. 12, pp. 2406–2413, 2011, doi: 10.1016/j.wasman.2011.07.022.

[11] K. Kawai and T. Tasaki, “Revisiting estimates of municipal solid waste generation per capita and their reliability,” J. Mater. Cycles Waste Manag., vol. 18, pp. 1–13, Jan. 2016, doi: 10.1007/s10163-015-0355-1.

[12] M. Haraguchi, A. Siddiqi, and V. Narayanamurti, “Stochastic cost-benefit analysis of urban waste-to-energy systems,” J. Clean. Prod., vol. 224, pp. 751–765, Jul. 2019, doi: 10.1016/j.jclepro.2019.03.099.

[13] K. L. P. Nguyen, Y. H. Chuang, H. W. Chen, and C. C. Chang, “Impacts of socioeconomic changes on municipal solid waste characteristics in Taiwan,” Resour. Conserv. Recycl., vol. 161, Oct. 2020, doi: 10.1016/j.resconrec.2020.104931.

[14] Z. Ceylan, S. Bulkan, and S. Elevli, “Prediction of medical waste generation using SVR, GM (1,1) and ARIMA models: a case study for megacity Istanbul,” J. Environ. Heal. Sci. Eng., vol. 18, no. 2, pp. 687–697, Dec. 2020, doi: 10.1007/s40201-020-00495-8.

[15] M. Bagheri, R. Esfilar, M. S. Golchi, and C. A. Kennedy, “A comparative data mining approach for the prediction of energy recovery potential from various municipal solid waste,” Renew. Sustain. Energy Rev., vol. 116, Dec. 2019, doi: 10.1016/j.rser.2019.109423.

[16] P. Nowakowski and T. Pamuła, “Application of deep learning object classifier to improve e-waste collection planning,” Waste Manag., vol. 109, pp. 1–9, 2020, doi: 10.1016/j.wasman.2020.04.041.

[17] M. W. Rahman, R. Islam, A. Hasan, N. I. Bithi, M. M. Hasan, and M. M. Rahman, “Intelligent waste management system using deep learning with IoT,” J. King Saud Univ. - Comput. Inf. Sci., Sep. 2020, doi: 10.1016/j.jksuci.2020.08.016.

[18] Z. Ye, J. Yang, N. Zhong, X. Tu, J. Jia, and J. Wang, "Tackling environmental challenges in pollution controls using artificial intelligence: A review," Science of the Total Environment, vol. 699. Elsevier, Jan. 10, 2020, doi: 10.1016/j.scitotenv.2019.134279.

[19] L. Chhay, M. A. H. Reyad, R. Suy, M. R. Islam, and M. M. Mian, "Municipal solid waste generation in China: influencing factor analysis and multi-model forecasting," J. Mater. Cycles Waste Manag., vol. 20, no. 3, pp. 1761–1770, 2018, doi: 10.1007/s10163-018-0743-4.

[20] M. Z. Joharestani, C. Cao, X. Ni, B. Bashir, and S. Talebiesfandarani, "PM2.5 prediction based on random forest, XGBoost, and deep learning using multisource remote sensing data," Atmosphere (Basel)., vol. 10, no. 7, p. 373, Jul. 2019, doi: 10.3390/atmos10070373.

[21] W. Xia, Y. Jiang, X. Chen, and R. Zhao, "Application of machine learning algorithms in municipal solid waste management: A mini review," Waste Management and Research. SAGE PublicationsSage UK: London, England, pp. 1–16, Jul. 16, 2021, doi: 10.1177/0734242X211033716.

[22] G. L. Huang, J. He, Z. Xu, and G. Huang, "A combination model based on transfer learning for waste classification," Concurr. Comput. , vol. 32, no. 19, pp. 1–12, 2020, doi: 10.1002/cpe.5751.

[23] K. Ahmad, K. Khan, and A. Al-Fuqaha, "Intelligent Fusion of Deep Features for Improved Waste Classification," IEEE Access, vol. 8, pp. 96495–96504, 2020, doi: 10.1109/ACCESS.2020.2995681.

[24] A. A. A. G. S. Altikat, "Intelligent solid waste classification using deep convolutional neural networks," Int. J. Environ. Sci. Technol., pp. 1–8, 2021, doi: 10.1007/s13762-021-03179-4.

[25] A. H. Vo, L. Hoang Son, M. T. Vo, and T. Le, "A Novel Framework for Trash Classification Using Deep Transfer Learning," IEEE Access, vol. 7, pp. 178631–178639, 2019, doi: 10.1109/ACCESS.2019.2959033.

[26] M. Valente, H. Silva, J. M. L. P. Caldeira, V. N. G. J. Soares, and P. D. Gaspar, "Detection of waste containers using computer vision," Appl. Syst. Innov., vol. 2, no. 1, pp. 1–13, 2019, doi: 10.3390/asi2010011.

[27] O. Adedeji and Z. Wang, "Intelligent waste classification system using deep learning convolutional neural network," Procedia Manuf., vol. 35, pp. 607–612, 2019, doi: 10.1016/j.promfg.2019.05.086.

[28] M. Toğaçar, B. Ergen, and Z. Cömert, "Waste classification using AutoEncoder network with integrated feature selection method in convolutional neural network models," Meas. J. Int. Meas. Confed., vol. 153, 2020, doi: 10.1016/j.measurement.2019.107459.

[29] D. Ziouzios, D. Tsiktsiris, N. Baras, and M. Dasygenis, "A Distributed Architecture for Smart Recycling Using Machine Learning," Futur. Internet, vol. 12, no. 9, p. 141, 2020, doi: 10.3390/fi12090141.

[30] Y. Chu, C. Huang, X. Xie, B. Tan, S. Kamal, and X. Xiong, "Multilayer hybrid deep-learning method for waste classification and recycling," Comput. Intell. Neurosci., vol. 2018, pp. 1–9, 2018, doi: 10.1155/2018/5060857.

[31] M. Cubillos, "Multi-site household waste generation forecasting using a deep learning approach," Waste Manag., vol. 115, pp. 8–14, 2020, doi: 10.1016/j.wasman.2020.06.046.

[32] D. Niu, F. Wu, S. Dai, S. He, and B. Wu, "Detection of long-term effect in forecasting municipal solid waste using a long short-term memory neural network," J. Clean. Prod., vol. 290, pp. 1–8, 2021, doi: 10.1016/j.jclepro.2020.125187.

[33] A. Hussain et al., "Waste Management and Prediction of Air Pollutants Using IoT and Machine Learning Approach," Energies, vol. 13, no. 15, pp. 3930–3951, 2020.

[34] F. Fasano, A. S. Addante, B. Valenzano, and G. Scannicchio, "Variables Influencing per Capita Production , Separate Collection , and Costs of Municipal Solid Waste in the Apulia Region (Italy): An Experience of Deep Learning," Int. J. Environ. Res. Public Health, vol. 18, no. 2, pp. 752–774, 2021.

[35] L. A. Akanbi, A. O. Oyedele, L. O. Oyedele, and R. O. Salami, "Deep learning model for Demolition Waste Prediction in a circular economy," J. Clean. Prod., vol. 274, no. 2020, 2020, doi: 10.1016/j.jclepro.2020.122843.

[36] Z. Kang, J. Yang, G. Li, and Z. Zhang, "An Automatic Garbage Classification System Based on Deep Learning," IEEE Access, vol. 8, pp. 140019–140029, 2020, doi: 10.1109/ACCESS.2020.3010496.

[37] M. Anjum and M. S. Umar, "Garbage localization based on weakly supervised learning in Deep Convolutional Neural Network," in Proceedings - IEEE 2018 International Conference on Advances in Computing, Communication Control and Networking, ICACCCN 2018, Oct. 2018, pp. 1108–1113, doi: 10.1109/ICACCCN.2018.8748568.

[38] R. N. Torres and P. Fraternali, "Learning to identify illegal landfills through scene classification in aerial images," Remote Sens., vol. 13, no. 22, pp. 1–21, Nov. 2021, doi: 10.3390/rs13224520.

[39] F. Zhang, C. Cao, C. Li, Y. Liu, and D. Huisingh, "A systematic review of recent developments in disaster waste management," J. Clean. Prod., vol. 235, pp. 822–840, 2019, doi: 10.1016/j.jclepro.2019.06.229.

[40] B. Kitchenham and S. Charters, "Guidelines for performing systematic literature reviews in software engineering," in Technical report, Ver. 2.3 EBSE Technical Report. EBSE, 2007, p. 65.

[41] M. Abdallah, M. Abu Talib, S. Feroz, Q. Nasir, H. Abdalla, and B. Mahfood, "Artificial intelligence applications in solid waste management: A systematic research review," Waste Manag., vol. 109, pp. 231–246, 2020, doi: 10.1016/j.wasman.2020.04.057.

[42] M. Staples and M. Niazi, "Systematic review of organizational motivations for adopting CMM-based SPI," Inf. Softw. Technol., vol. 50, no. 7–8, pp. 605–620, 2008.

[43] W. Reim, V. Parida, and D. Örtqvist, "Product-Service Systems (PSS) business models and tactics - A systematic literature review," J. Clean. Prod., vol. 97, pp. 61–75, Jun. 2015, doi: 10.1016/j.jclepro.2014.07.003.

[44] United Nations, Human Development Report 2020. 2020.

[45] A. Annarelli, C. Battistella, and F. Nonino, "Product service system: A conceptual framework from a systematic review," Journal of Cleaner Production, vol. 139. Elsevier Ltd, pp. 1011–1032, Dec. 15, 2016, doi: 10.1016/j.jclepro.2016.08.061.

[46] T. J. Sheng et al., "An Internet of Things Based Smart Waste Management System Using LoRa and Tensorflow Deep Learning Model," IEEE Access, vol. 8, pp. 148793–148811, 2020, doi: 10.1109/ACCESS.2020.3016255.

[47] J. Bai, S. Lian, Z. Liu, K. Wang, and D. Liu, "Deep learning based robot for automatically picking up garbage on the grass," IEEE Trans. Consum. Electron., vol. 64, no. 3, pp. 382–389, 2019.

[48] S. Jagtap, C. Bhatt, J. Thik, and S. Rahimifard, "Monitoring potato waste in food manufacturing using image processing and internet of things approach," Sustain., vol. 11, no. 11, pp. 1–12, 2019, doi: 10.3390/su11113173.

[49] W. L. Mao, W. C. Chen, C. T. Wang, and Y. H. Lin, "Recycling waste classification using optimized convolutional neural network," Resour. Conserv. Recycl., vol. 164, no. August 2020, p. 105132, 2021, doi: 10.1016/j.resconrec.2020.105132.

[50] P. Ping, G. Xu, E. Kumala, and J. Gao, "Smart Street Litter Detection and Classification Based on Faster R-CNN and Edge Computing," Int. J. Softw. Eng. Knowl. Eng., vol. 30, no. 4, pp. 537–553, 2020, doi: 10.1142/S0218194020400045.

[51] P. Zhang, Q. Zhao, J. Gao, W. Li, and J. Lu, "Urban Street Cleanliness Assessment Using Mobile Edge Computing and Deep Learning," IEEE Access, vol. 7, pp. 63550–63563, 2019, doi: 10.1109/ACCESS.2019. 2914270.

[52] K. M. Bobulski J, "Waste classification system using image processing and convolutional neural networks," Int. Work. Artif. Neural Networks, 2019 Jun 12, Springer, Cham., pp. 350–361, 2019, [Online]. Available: http://dx.doi.org/10.1007/978-3-030-20518-8_30.

[53] S. Kumar, D. Yadav, H. Gupta, O. P. Verma, I. A. Ansari, and C. W. Ahn, "A novel yolov3 algorithm-based deep learning approach for waste segregation: Towards smart waste management," Electron., vol. 10, no. 1, pp. 1–20, 2021, doi: 10.3390/electronics10010014.

[54] S. Liang and Y. Gu, "A deep convolutional neural network to simultaneously localize and recognize waste types in images," Waste Manag., vol. 126, pp. 247–257, 2021, doi: 10.1016/j.wasman.2021. 03.017.

[55] D. O. Melinte, A. M. Travediu, and D. N. Dumitriu, "Deep convolutional neural networks object detector for real-time waste identification," Appl. Sci., vol. 10, no. 20, pp. 1–18, 2020, doi: 10.3390/app10207301.

[56] P. Davis, F. Aziz, M. T. Newaz, W. Sher, and L. Simon, "The classification of construction waste material using a deep convolutional neural network," Autom. Constr., vol. 2021, 2021, doi: 10.1016/j.autcon.2020.103481.

[57] H. Wang, Y. Li, L. M. Dang, J. Ko, D. Han, and H. Moon, "Smartphone-based bulky waste classification using convolutional neural networks," Multimed. Tools Appl., vol. 79, no. 39–40, pp. 29411–29431, 2020, doi: 10.1007/s11042-020-09571-5.

[58] O. I. Funch, R. Marhaug, S. Kohtala, and M. Steinert, "Detecting glass and metal in consumer trash bags during waste collection using convolutional neural networks," Waste Manag., vol. 119, pp. 30–38, 2021, doi: 10.1016/j.wasman.2020.09.032.

[59] M. H. Huynh, P. T. Pham-Hoai, A. K. Tran, and T. D. Nguyen, "Automated Waste Sorting Using Convolutional Neural Network," Proc. - 2020 7th NAFOSTED Conf. Inf. Comput. Sci. NICS 2020, pp. 102–107, 2020, doi: 10.1109/NICS51282.2020.9335897.

[60] V. P. Brintha, R. Rekha, J. Nandhini, N. Sreekaarthick, and B. Ishwaryaa, "Automatic Classi fi cation of Solid Waste Using Deep Learning," in Proceedings of International Conference on Artificial Intelligence, Smart Grid and Smart City Applications, 2019, pp. 881–889, doi: 10.1007/978-3-030-24051-6_83.

[61] H. Panwar et al., "AquaVision: Automating the detection of waste in water bodies using deep transfer learning," Case Stud. Chem. Environ. Eng., vol. 2, Sep. 2020, doi: 10.1016/j.cscee.2020.100026.

[62] W. Sterkens, D. Diaz-Romero, T. Goedemé, W. Dewulf, and J. R. Peeters, "Detection and recognition of batteries on X-Ray images of waste electrical and electronic equipment using deep learning," Resour. Conserv. Recycl., vol. 168, May 2021, doi: 10.1016/j.resconrec.2020. 105246.

[63] O. Youme, T. Bayet, J. M. Dembele, and C. Cambier, "Deep Learning and Remote Sensing: Detection of Dumping Waste Using UAV," in Procedia Computer Science, Jan. 2021, vol. 185, pp. 361–369, doi: 10.1016/j.procs.2021.05.037.

[64] J. Bobulski and M. Kubanek, "Deep Learning for Plastic Waste Classification System," Appl. Comput. Intell. Soft Comput., vol. 2021, pp. 1–7, 2021, doi: 10.1155/2021/6626948.

[65] C. Shi, C. Tan, T. Wang, and L. Wang, "A waste classification method based on a multilayer hybrid convolution neural network," Appl. Sci., vol. 11, no. 18, pp. 1–19, Sep. 2021, doi: 10.3390/app11188572.

[66] C. Wang, J. Qin, C. Qu, X. Ran, C. Liu, and B. Chen, "A smart municipal waste management system based on deep-learning and Internet of Things," Waste Manag., vol. 135, pp. 20–29, Nov. 2021, doi: 10.1016/j.wasman.2021.08.028.

[67] B. M. Allan, D. G. Nimmo, D. Ierodiaconou, J. VanDerWal, L. P. Koh, and E. G. Ritchie, "Futurecasting ecological research: the rise of technoecology," Ecosphere, vol. 9, no. 5, May 2018, doi: 10.1002/ecs2.2163.

[68] J. J. Valletta, C. Torney, M. Kings, A. Thornton, and J. Madden, "Applications of machine learning in animal behaviour studies," Animal Behaviour, vol. 124. Academic Press, pp. 203–220, Feb. 01, 2017, doi: 10.1016/j.anbehav.2016.12.005.

[69] I. Goodfellow, Y. Bengio, and A. Courville, Deep learning. 2016.

[70] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015, doi: 10.1038/nature14539.

[71] A. Kumar, C. P. Gandhi, Y. Zhou, R. Kumar, and J. Xiang, "Improved deep convolution neural network (CNN) for the identification of defects in the centrifugal pump using acoustic images," Appl. Acoust., vol. 167, p. 107399, Oct. 2020, doi: 10.1016/j.apacoust.2020.107399.

[72] F. Seide, A. A.-P. of the 22nd A. SIGKDD, and U. 2016, "CNTK: Microsoft's open-source deep-learning toolkit," in Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, 2016, pp. 2135–2135, [Online]. Available: https://dl.acm.org/doi/abs/10.1145/2939672.2945397.

[73] C. J. Abadi, Martín, Barham P, "{TensorFlow} A system for large-scale machine learning," in 12th USENIX symposium on operating systems design and implementation (OSDI 16), 2016, pp. 265–283, [Online]. Available: https://www.usenix.org/conference/osdi16/technical-sessions/presentation/abadi.

[74] J. Nickolls and W. J. Dally, "The GPU computing era," IEEE Micro, vol. 30, no. 2, pp. 56–69, 2010, doi: 10.1109/MM.2010.41.

[75] S. Majchrowska et al., "Deep learning-based waste detection in natural and urban environments," Waste Manag., vol. 138, pp. 274–284, Feb. 2022, doi: 10.1016/j.wasman.2021.12.001.

[76] M. Abbasi and A. El Hanandeh, "Forecasting municipal solid waste generation using artificial intelligence modelling approaches.," Waste Manag., vol. 56, pp. 13–22, 2016, doi: 10.1016/j.wasman.2016.05.018.

[77] H. Niska and A. Serkkola, "Data analytics approach to create waste generation profiles for waste management and collection," Waste Manag., vol. 77, pp. 477–485, Jul. 2018, doi: 10.1016/j.wasman.2018.04.033.

[78] C. Birgen, E. Magnanelli, P. Carlsson, Ø. Skreiberg, J. Mosby, and M. Becidan, "Machine learning based modelling for lower heating value prediction of municipal solid waste," Fuel, vol. 283, Jan. 2021, doi: 10.1016/j.fuel.2020.118906.

[79] B. Fallah, K. T. W. Ng, H. L. Vu, and F. Torabi, "Application of a multi-stage neural network approach for time-series landfill gas modeling with missing data imputation," Waste Manag., vol. 116, pp. 66–78, Oct. 2020, doi: 10.1016/j.wasman.2020.07.034.

[80] J. Soto-Paz et al., "A New Approach for the Optimization of Biowaste Composting Using Artificial Neural Networks and Particle Swarm Optimization," Waste and Biomass Valorization, vol. 11, no. 8, pp. 3937–3951, Aug. 2020, doi: 10.1007/s12649-019-00716-8.

[81] D. Wang and Y. Shang, "A new active labeling method for deep learning," in Proceedings of the International Joint Conference on Neural Networks, Sep. 2014, pp. 112–119, doi: 10.1109/IJCNN.2014.6889457.