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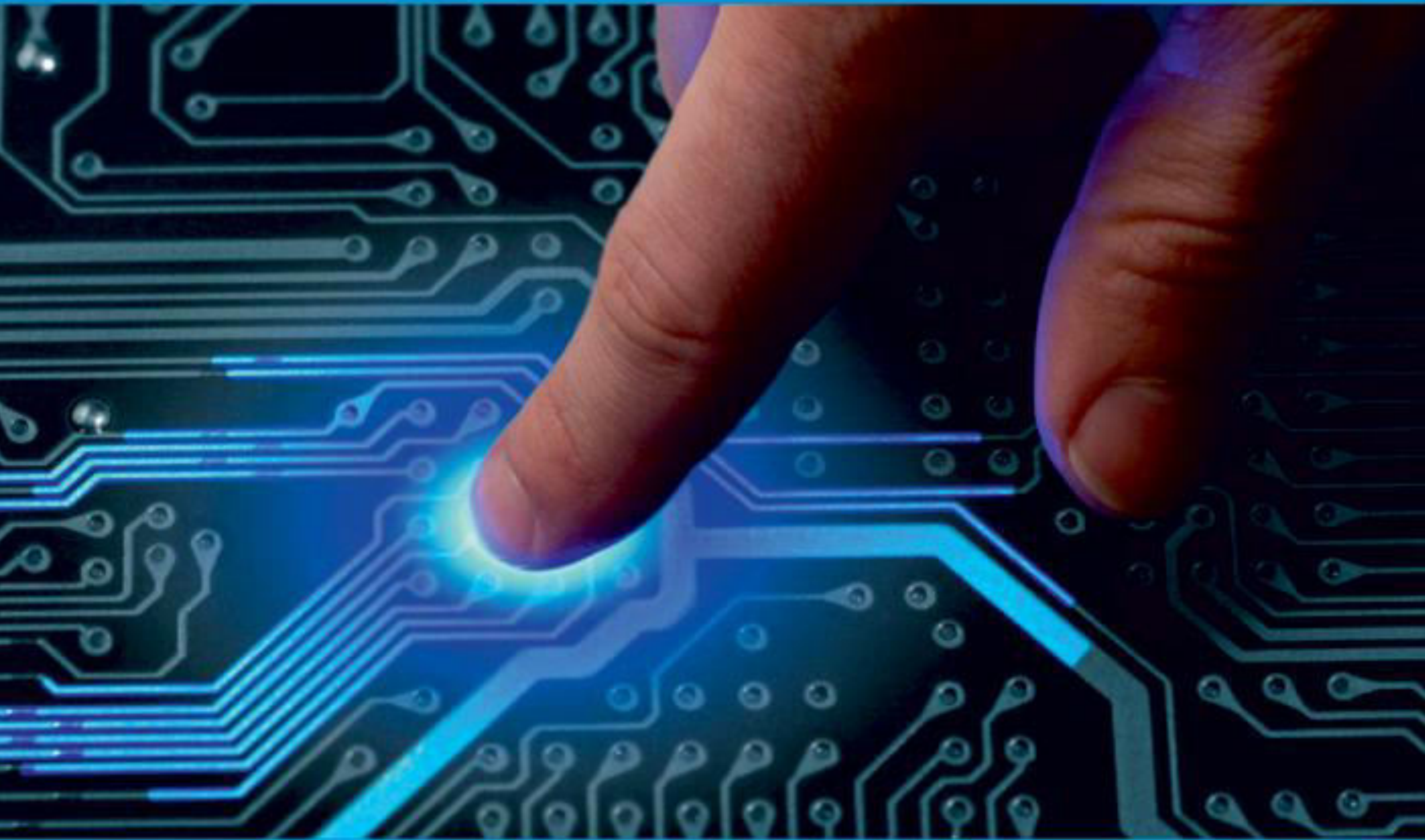

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Survey: Smart Handling of Bio Medical Waste from Intelligent Deep Learning and IOT

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ABSTRACT: Hospitals produce a massive amount of potentially dangerous waste. To enable early intervention and optimal waste processing, efficient management of medical waste necessitates not only perfect segregation but also real-time monitoring and alerting systems. This survey suggests an integrated approach that combines Internet of Things (IoT) technology, image processing, embedded systems hardware, and deep learning. The deep learning approach will be used to identify medical waste. The biomedical waste management system is made up of several interconnected processes that perform a range of intricate tasks. Deep learning (DL) has drawn more attention recently as a potential alternative to traditional computational methods for solving a range of biomedical waste management issues. A great deal of research has been published in this area as a consequence of researchers' focus, especially in recent years. A few thorough surveys on garbage detection and segregation have been conducted, according to the literature. Nevertheless, no research has looked at how deep learning and IOT may be used to address waste management issues across a range of industries and emphasize the datasets that are available for trash detection and classification across these industries. To improve the classification process' accuracy, image processing techniques are applied once a deep learning model has been trained on a variety of datasets.

KEYWORDS*:* Deep Learning, Dataset, BMW, Clinical waste identification & segregation, Deep Learning models

I.INTRODUCTION

Hospitals and other healthcare institutions must make sure that their waste management procedures comply with applicable rules and that appropriate handling methods are followed in order to reduce the risk of mishaps and injuries with biological waste. This might entail providing waste management training to staff members, utilizing suitable storage facilities and containers, and labelling and packing waste products appropriately before they are sent for disposal or treatment [1]. Hospitals handle the routine disposal of medical waste through the use of a Bio-Medical waste management system. It delivers hospital medical waste on a daily basis. Medical supplies, such as needles, plastic, glassware, medical apparel, expired drugs, and human waste, are handled by a different system. In light of this, they utilize the Biomedical Waste Management Centre to receive and properly dispose of routine medical waste from their hospitals. Medical waste should never be disposed of by a hospital. It is against the law, and the accountable hospital is required to properly segregate and transport the medical waste to the biomedical waste treatment facility [2]. Bandages, plastic papers, pus that has been discarded, syringes, glucose drip bottles, and other hazardous medical wastes are now sorted by hand, which has long-term health effects including cancer, infectious illnesses, and TB [3]. An extremely inefficient and expensive daily schedule drives the operation of traditional waste management systems. Because individuals do not recycle their garbage correctly, the current recycle bin has also demonstrated its inefficiency to the general public. With the advancement of Deep Learning (DL) and the Internet of Things (IoT), smart sensors integrated into the system can replace the conventional trash management system, enabling improved waste management through real-time monitoring. This study aims to develop an intelligent waste separation and management procedure for medical waste material based on the Internet of Things (IoT). It makes use of sensor devices to identify rubbish in dustbins. Sensors will separate its waste materials as soon as they are discovered. Immediately, data is moved to cloud databases using IoT, which facilitates the smart and effective removal of waste from the trash can. The suggested method will stop toxic wastes from claiming countless lives.

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Figure 1: Treatment of bio medical waste as per the colour code

The treatment of biomedical waste is a critical aspect of healthcare management to prevent the spread of infections and protect public health. The color-coding system plays a vital role in the proper segregation and disposal of biomedical waste. According to the World Health Organization's standard, different colors signify specific types of waste, ensuring that each category is treated appropriately.

Yellow bins or containers are designated for anatomical waste, encompassing tissues, organs, and body parts. Red bins are reserved for sharps waste, such as needles and syringes. Blue bins are used for items contaminated with drugs or pharmaceutical products. Black bins accommodate non-sharp, non-anatomical waste, including gloves and tubing contaminated with blood or body fluids. White bins are allocated for waste from microbiological and biotechnological laboratories. Yellow-blue bins are specifically designed for radioactive waste, while black-white bins cater to general waste that doesn't fall into the aforementioned categories.

The integration of the Internet of Things (IoT) and deep learning technologies offers significant advantages in the handling of biomedical waste. IoT devices can be installed in waste bins to enable real-time monitoring. These devices can track the fill-level of the bins, ensuring timely disposal and preventing overflows that could lead to contamination. Additionally, IoT sensors can provide data on temperature and other environmental conditions, helping to maintain optimal storage conditions for certain types of biomedical waste.

Deep learning algorithms can be employed to analyze the data collected by IoT devices. Machine learning models can identify patterns and predict fill-level trends, optimizing waste management schedules and resource allocation. This predictive capability enhances the efficiency of waste collection, reduces operational costs, and minimizes the risk of exposure to hazardous materials.

Furthermore, the combination of IoT and deep learning allows for the implementation of smart waste management systems. These systems can automate waste segregation processes by analyzing the types of waste generated in healthcare facilities. Automated sorting based on the color-coded categories can streamline the disposal process, ensuring that each type of waste undergoes the appropriate treatment, be it incineration, autoclaving, or other disposal methods compliant with environmental regulations.The integration of IoT and deep learning technologies enhances this process by offering real-time monitoring, predictive analytics, and smart waste management solutions, ultimately contributing to more efficient and environmentally responsible biomedical waste handling practices in healthcare facilities.

II.RELATED SURVEY

Hospital trash transportation and treatment is a labour-intensive, hazardous, and contagious process that exposes workers to biohazardous and medical waste. The maximum duration for which hospital biological waste should be stored is 24 to 36 hours. Frequently and safely disposing of trash is important to help the hospital have a clean environment for its visitors, staff, and patients. Using RTOS-based Multifunctional Bins, robotic garbage transfer is

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used to achieve this. The garbage gathered from smart bins is comprised of microcontrollers based on Arduino Uno equipped with UV sterilizing lamps and sensors. Simple to use and move about securely in an area with plenty of people. These containers are made specifically to accommodate different types of commodities that need to be moved This covers the protection of contamination using an integrated UV light system to control contamination on the outside and preserve a secure area for handling garbage [1]. Designing a Clinical Waste Storage System with a Contamination Prevention Mechanism using UV light and an Arduino microcontroller involves integrating various components to ensure safe and efficient waste management. Hospitals' regular medical waste will be accepted by the Biomedical Waste Management Centre, which will dispose of it properly. Medical waste should never be disposed of by a hospital. It is against the law, and the accountable hospital is required to properly segregate and transport the medical waste to the biomedical waste treatment facility. Develope an intelligent machine learning model to handle various biomedical wastes and separate them according to medical regulations. Hospitals dispose of their medical waste by securely transporting and burning it [2]. Implementing a smart handling system for biomedical waste with intelligent machine learning models involves combining hardware and software solutions to efficiently segregate and manage biomedical waste. The Deep Learning method will be used to detect waste; a model will be developed to differentiate between different types of medical waste. garbage may be readily separated and disposed of in the garbage bin by using a flip attachment on a motor. Depending on the type of trash identified, two flips open, and the rubbish is separated into compartments with four distinct chambers. The garbage level may be updated with corresponding times and dates using web apps that are IoT-based. Consequently, it is possible to prevent garbage from overflowing the trash container. Here, medical waste is promptly and correctly separated to cut down on manual work and prevent the spread of illness throughout hospitals [3]. An IoT integrated sensor technology system for the enhancement of hospital waste segregation and management combines smart waste bins with various sensors, communication modules, and data processing capabilities. The system aims to improve efficiency, reduce human intervention, and enhance waste segregation in healthcare facilities. Key components include smart waste bins equipped with weight, image, and gas sensors, along with actuators for automatic compartmentalization. Data collected from these sensors are transmitted to a cloud platform for analysis, allowing for real-time monitoring, waste type identification, and potential hazard detection. The system provides feedback through displays on the bins and interfaces for users and administrators, facilitating effective waste disposal practices. Additionally, the integration of notifications, alerts, and data logging supports compliance with regulations, enables timely maintenance, and ensures optimized waste management in hospitals. The accuracy level of the Single Shot MultiBox Detector (SSD) approach applied with TensorFlow framework is equally low. Other research' findings, which employed the YOLOv4 approach, demonstrated that this model's accuracy decreased when it ran on a Raspberry Pi. You Only Look Once (YOLO) is an intriguing and potentially useful concept for item classification in general. Consequently, this study suggested developing a real-time hazardous waste categorization system based on the YOLOv5 approach. The development of a COVID medical waste object classification system using YOLOv5 on Raspberry Pi involves implementing a computer vision solution to identify and classify COVID-related medical waste items. YOLOv5 (You Only Look Once version 5) is a popular real-time object detection algorithm that can be optimized for resource-constrained environments like the Raspberry Pi. A growing issue is the collection of medical waste. Rebuilding these overcrowded landfills is impossible when unwanted trash is dumped on the outskirts of towns and cities. In addition, the physical labour that the present technology necessitates might cause a persistent sickness in its user. Creating an automated system to save countless lives and build a cleaner, greener society are only two of the proposed system's admirable objectives. An intelligent dry and wet waste separation and management procedure of medical waste material is the primary objective of this study, which is based on the Internet of Things. By employing sensor devices, it is able to identify rubbish in dustbins. Its waste products will be segregated using sensors as soon as they are recognized [5]. The disposal method's lack of effort and the virus's transmissible nature put both the disposer and front-line health professionals' safety at danger. Therefore, a robotic arm-based system for autonomously sorting medical waste is proposed as a means of reducing the transmission of contagious illnesses. Voice instructions may be used to control the robotic arm, and there are two modes for the segregating operation: automatic and manual. A ROS-based Voice Controlled Robotic Arm for Automatic Segregation of Medical Waste using YOLOv3 is a system that combines the Robot Operating System (ROS), voice control, and computer vision to autonomously segregate medical waste. After classifying and detecting medical waste using the YOLOv3 algorithm, the Robot Operating System platform is used to pick up and deposit the waste object into color-coded bins. The medical waste has been divided into four categories for this study, and a color-coded container has been assigned to each category [6]. This biomedical waste must be collected from isolation units, laboratory facilities, COVID testing centers, and quarantine wards. It must be stored separately and turned over right away to the Common Biomedical Waste Treatment and Disposal Facility (CBWTF). In order to ensure that the sanitary personnel involved in this collection are regularly cleaning and properly disposing of this hazardous biological waste, this article suggests an Internet of Things (IoT) enabled BIOBIN [7]. The goal is to create a deep learning model based on TensorFlow and the

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LoRa communication protocol to create an intelligent waste management system. Tensorflow handles real-time object recognition and classification after receiving sensor data via LoRa. The servo motors in the bin regulate the many divisions that are designed to separate garbage, such as the general waste compartment, the paper, plastic, and metal sections. Using a pre-trained object detection model, the TensorFlow framework performs object recognition and trash categorization. A camera attached to the Raspberry Pi 3 Model B+, which serves as the main processing unit, is utilized to detect objects. The object identification model is trained using waste picture data to create a frozen inference graph [8]. An Internet of Things (IoT) based smart waste management system using LoRa (Long Range) and a TensorFlow deep learning model is designed to efficiently monitor and manage waste bins in a connected environment. This system integrates IoT technologies, long-range communication, and deep learning for real-time waste detection and management. This IoT-based smart waste management system combines long-range communication, deep learning, and cloud computing to create an intelligent waste management solution. Regular updates and maintenance are essential for optimal performance and adaptability to changing waste disposal needs. Linked waste sorting equipment with LoRaWAN communication networks created using the Internet of Things to produce a system that provides graphical interface monitoring, environmental monitoring, and automated garbage can operation. The sorts of waste dumped in garbage cans are identified by the system using proximity sensors of the electrostatic capacitance type. Moreover, it has an embedded motor and smart devices that can open and close insertion points automatically, sort waste, start automatic garbage compression, monitor water levels, and send out alerts when the water level goes above a predetermined threshold [9]. An Environmental Monitoring and Smart Garbage Sorting System based on LoRa (Long Range) wireless transmission technology is designed to enhance waste management practices, improve efficiency, and contribute to environmental sustainability. This system integrates IoT (Internet of Things) sensors, LoRa communication, and smart garbage sorting technologies to monitor environmental conditions and automate waste sorting processes. This Environmental Monitoring and Smart Garbage Sorting System using LoRa technology provide an integrated approach to waste management, contributing to resource optimization and a cleaner environment. Researchers have made a lot of effort to suggest different ways to get around this difficulty, yet the issue still exists. The separation of various waste kinds is the main issue encountered while developing an intelligent garbage collecting and monitoring system. The trash is still being separated by hand, which is damaging to the segregator itself. This describes an automated trash segregator system that can distinguish between and store moist and dry garbage in various locations [10]. An Automatic Waste Segregator, as an integral part of a Smart Bin for a waste management system in a Smart City, aims to enhance the efficiency of waste collection, reduce contamination, and promote sustainable waste disposal practices. This system integrates cutting-edge technologies to automate the segregation process and improve overall waste management. The amount of biomedical waste produced annually has increased by almost 8% over the previous year. Wireless solutions are being introduced in an attempt to automate trash management. Plans for segregation are suggested in order to optimize waste recycling and ensure appropriate management of non-recyclable garbage. A large range of wastes, including biological waste, would not be supported by that categorization. As a result, this kind of garbage is handled differently. Thus, a waste of this kind needs its own management unit. It examines the techniques that are currently being followed by different nations as well as the different technologies that may be used to automate these procedures and handle biohazardous waste with care [11]. An Internet of Things (IoT) based biomedical waste classification, quantification, and management system is designed to enhance the efficiency, safety, and compliance of biomedical waste disposal in healthcare facilities. The integration of IoT technologies facilitates real-time monitoring, classification, and quantification of biomedical waste, leading to optimized waste management practices. The system's purpose is to gather information and transmit it over a wireless mesh network. In order to increase operating duration and minimize power consumption, the system also uses the duty cycle approach. An open air setting was used to test the Smartbin technology. [12]. Litter bin use and daily seasonality statistics were obtained using tested, gathered data, and sense-making techniques. Litter bin suppliers and cleaning companies may make more informed decisions and boost efficiency with this kind of information. An intelligent and networked solution, a smart waste management system is made to maximize garbage collection, boost productivity, and support environmentally friendly activities.

Ref	Year	H/w	S/w & Technology	Accuracy
1	2023	Arduino Microcontroller, Uv-C Light System, Sensors, Power Supply	RTOS	NA
2	2023	Na	Machine Learning	NA

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3	2023	Image Sensors, Flip Attachment And Motor,	IOT, Deep Learning	NA
4	2023	Raspberry Pi 3b+, Camera Module	YOLOv5, Tensorflow, Raspberry Pi OS, Python	96%
5	2022	Sensor, Micro Controllers, Power Supply	IOT, Embeddeed C, Machine Learning	NA
6	2022	Robotic Arm, Microcontroller, Camera	Yolo V3, ROS	82.5%
7	2021	IOT Enabled BIOBIN, Sensors	IOT, Embedded C	NA
8	2020	Raspberry Pi 3 Model B+, Camera Module, Ultrasonic Sensors, Servo Motor, RFID Module	TensorFlow Framewor, LoRa Communication Protocol, Python, IOT	NA
9	2020	Electrostatic Capacitance-Type Proximity Sensors, Embeddeed Motor , Smart Devices	Embedded C, LoRAWan, **C#** Graphical Monitoring Interface	NA
10	2019	Sensor, Microcontroller	Machine Learning, Python	NA
11	2017	RFID , Biometric Access Control Systems, Wireless Sensor Networks, Automated Waste Segregation Systems, Data Storage & Processing Servers	IOT	NA
12	2015	Ultrasonic Sensor, Microcontroller	Centralized Server or Cloud Platform	NA

III.DEEP LEARNING NETWORK MODELS

The fields of trash sorting and medical picture analysis have advanced significantly thanks to deep learning-based algorithms.

A. Convolutional Neural Network(CNN)

Convolutional Neural Networks (CNNs) represent a potent category of deep learning models that are well tailored for tasks that need visual input, such object identification and picture recognition. Convolutional layers, which automatically extract hierarchical features from incoming data by applying filters, are a defining aspect of its design. CNNs effectively record spatial hierarchies by utilizing weight sharing and pooling layers, which enables them to identify patterns at various abstraction levels. ReLU is one example of a non-linear activation function that adds flexibility and helps the network discover intricate links in the input. Higher layers of the hierarchical feature learning process gradually capture more abstract and complex aspects, while lower layers identify fundamental elements like

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edges and textures. CNNs have demonstrated exceptional performance and versatility in a wide range of computer vision applications.

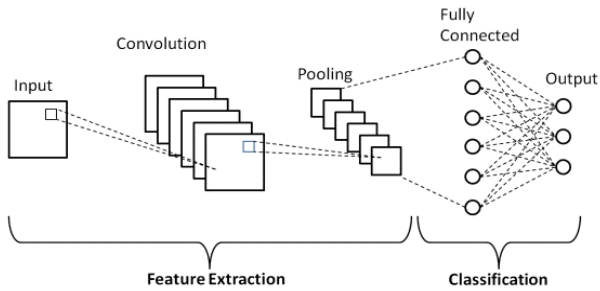

Figure 2: Architecture of CNN

The journey begins with the input layer, where raw data, such as an image matrix, is fed into the network. Convolutional layers follow, applying filters to detect patterns and features in local regions of the input. Activation layers introduce non-linearity, crucial for the network to capture complex relationships. Pooling layers then down-sample the spatial dimensions, reducing computational complexity and enhancing translation invariance. These convolutional and pooling layers work in tandem to hierarchically extract features. Finally, fully connected layers integrate these learned features for high-level decision-making. A flattening layer reshapes the data before entering fully connected layers. The interplay between these layers allows CNNs to automatically learn and discern meaningful features, making them particularly adept at tasks involving visual information.

B. AlexNet

AlexNet, introduced in 2012 by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, marked a pivotal advancement in the field of deep learning and computer vision. As one of the early convolutional neural networks (CNNs) to gain widespread recognition, AlexNet significantly contributed to the success of deep learning in image classification tasks. Comprising eight layers, including five convolutional layers and three fully connected layers, AlexNet demonstrated the effectiveness of deep architectures in learning hierarchical features. Notably, the utilization of rectified linear units (ReLU) as activation functions and the incorporation of techniques like data augmentation and dropout played a crucial role in mitigating overfitting and enhancing generalization. AlexNet achieved a breakthrough performance in the ImageNet Large Scale Visual Recognition Challenge, showcasing the potential of deep learning models for large-scale image classification tasks. The success of AlexNet laid the foundation for subsequent advancements in deep neural networks and spurred the development of more sophisticated architectures, influencing the trajectory of modern computer vision research.

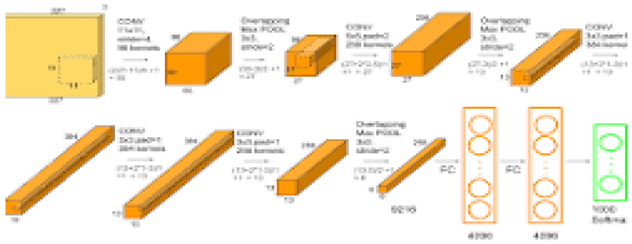

Figure 3: Architecture of AlexNet

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C.ResNet-50

ResNet-50, short for Residual Network with 50 layers, is a deep convolutional neural network architecture that was introduced by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in 2015. It represents a significant breakthrough in addressing the challenges of training very deep neural networks. The distinguishing feature of ResNet-50 is the use of residual blocks, which contain shortcut connections that skip one or more layers. These shortcuts enable the direct flow of information through the network, mitigating the vanishing gradient problem and facilitating the training of extremely deep models. ResNet-50 consists of 50 layers, including convolutional layers, batch normalization, and global average pooling, followed by fully connected layers for classification. The architecture demonstrated superior performance in image classification tasks, winning the ImageNet Large Scale Visual Recognition Challenge in 2015. ResNet-50 has since become a cornerstone in various computer vision applications, providing a robust and efficient framework for feature learning in deep neural networks. Its residual learning approach has inspired the design of even deeper networks, contributing to the evolution of modern deep learning architectures.

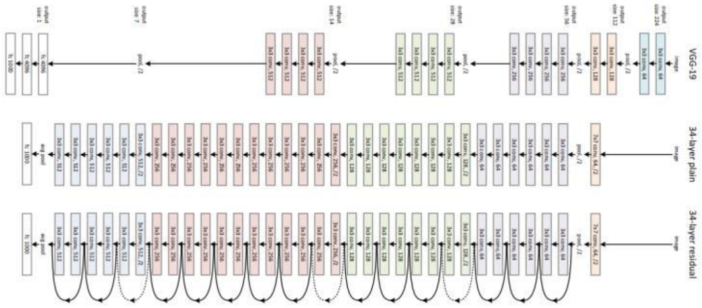

Figure 4: Architecture of ResNet-50

It Comprising 50 layers, it is structured around residual blocks, a key innovation introduced by Kaiming He and his colleagues in 2015. Each residual block contains a shortcut connection that skips one or more layers, allowing the direct flow of information through the network. This design addresses the degradation problem encountered in training deep networks and facilitates the learning of more discriminative features. The ResNet-50 architecture consists of convolutional layers, batch normalization, and global average pooling, culminating in fully connected layers for classification. The skip connections in residual blocks not only aid in gradient flow but also enable the training of significantly deeper networks. With its groundbreaking design, ResNet-50 has become a cornerstone in computer vision, showcasing the importance of residual learning and influencing subsequent advancements in deep neural network.

D. VGG

The VGG architecture, proposed by the Visual Geometry Group at the University of Oxford, is a deep convolutional neural network renowned for its simplicity and effectiveness in image classification tasks. Introduced in 2014 by researchers Karen Simonyan and Andrew Zisserman, VGGNet is characterized by its uniform structure, comprising a series of convolutional layers with small 3x3 filters, followed by max-pooling layers for spatial downsampling. The design philosophy of stacking multiple convolutional layers with small receptive fields allows VGG to capture complex hierarchical features in a more granular manner. The VGG architecture comes in different variants, with VGG16 and VGG19 being the most popular, differing in the depth of layers. While VGG's straightforward architecture makes it easy to understand and implement, it also leads to a large number of parameters, making training computationally intensive. Despite its simplicity, VGG demonstrated impressive performance in image classification competitions and served as a benchmark for subsequent deep learning models, contributing significantly to the evolution of convolutional neural networks in computer vision.

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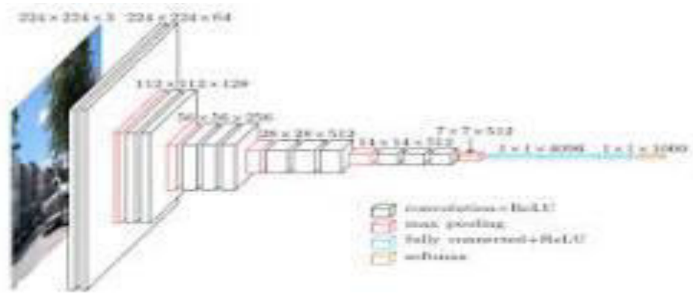

Figure 5: Architecture of VGG

The VGG (Visual Geometry Group) architecture is characterized by its straightforward and uniform layer structure. It consists of several convolutional and pooling layers, making it a prominent model for image classification. The standard VGG16 architecture, for instance, is comprised of 16 layers, including 13 convolutional layers and 3 fully connected layers. The convolutional layers primarily utilize 3x3 filters, enhancing the model's ability to capture intricate hierarchical features from the input data. These convolutional layers are followed by max-pooling layers, which reduce spatial dimensions and contribute to the model's translation invariance. The activation function employed is typically ReLU, introducing non-linearity into the network. The fully connected layers, placed at the end of the architecture, perform high-level reasoning and decision-making based on the learned features. Although the VGG architecture may result in a substantial number of parameters due to its depth, its simplicity has made it an influential model in the deep learning community, serving as a benchmark for subsequent convolutional neural network designs.

E. GoogleNet

GoogleNet, also known as Inception v1, represents a breakthrough in convolutional neural network (CNN) architectures and was introduced by Google researchers in 2014. Its innovative design is characterized by the extensive use of inception modules, which combine filters of varying sizes within the same layer. This architecture aims to capture features at different spatial scales efficiently. The inception modules employ 1x1, 3x3, and 5x5 convolutions, along with max-pooling, and concatenate their outputs. This design facilitates the network's ability to learn both fine-grained and global features simultaneously. To address computational efficiency and reduce the number of parameters, GoogleNet also incorporates 1x1 convolutions for dimensionality reduction. With a total of 22 layers, including auxiliary classifiers to aid in training, GoogleNet achieved notable success in the ImageNet Large Scale Visual Recognition Challenge. The Inception architecture has since evolved with subsequent versions, contributing to the development of more sophisticated models for various computer vision tasks.

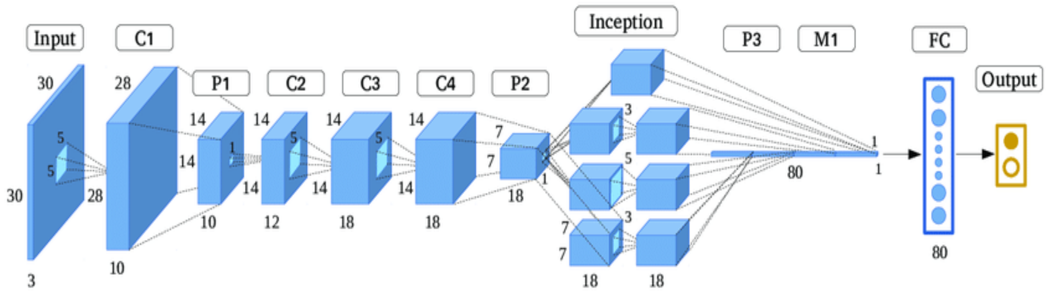

Figure 6: Architecture of GoogleNet

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Inception v1, is a pioneering deep neural network architecture that gained prominence for its innovative design and efficient handling of complex visual data. One of its key features is the extensive use of inception modules, which are designed to capture features at different spatial scales within the same layer. The architecture, introduced in 2014, consists of 22 layers, including these inception modules. Each inception module incorporates multiple parallel convolutional operations with different filter sizes (1x1, 3x3, and 5x5) and pooling operations. This design allows the network to learn and combine features at various levels of abstraction simultaneously. Additionally, 1x1 convolutions are employed for dimensionality reduction, aiding in computational efficiency and reducing the number of parameters. GoogleNet also introduced the concept of auxiliary classifiers, which are inserted into intermediate layers during training to address the vanishing gradient problem. This unique architecture not only demonstrated exceptional performance in image classification tasks, winning the ImageNet Large Scale Visual Recognition Challenge in 2014, but also influenced the development of subsequent neural network architectures, particularly those emphasizing parallelized feature extraction.

F.MobileNet

MobileNet is a family of neural network architectures specifically designed for efficient and lightweight deep learning on mobile and edge devices. It employs innovative techniques to balance computational efficiency with model accuracy. One key feature is the use of depthwise separable convolutions, breaking down the traditional convolutional layers into two distinct operations, namely depthwise convolution and pointwise convolution. This design significantly reduces the number of parameters and computations, making the model well-suited for resource-constrained devices. Additionally, MobileNet introduces hyperparameters like the "width multiplier" (alpha) and "resolution multiplier" (rho), allowing users to control the number of channels in each layer and scale down the spatial dimensions of the input image, further enhancing computational efficiency. The architecture also adopts a bottleneck structure, utilizing 1x1 convolutions to reduce input channel dimensions before applying depthwise separable convolutions. Furthermore, MobileNet often replaces fully connected layers with global average pooling at the end of the network, minimizing parameters and mitigating overfitting. With variants such as MobileNetV1, MobileNetV2, and MobileNetV3, this family of architectures has become a popular choice for real-time applications on devices with limited computational resources.

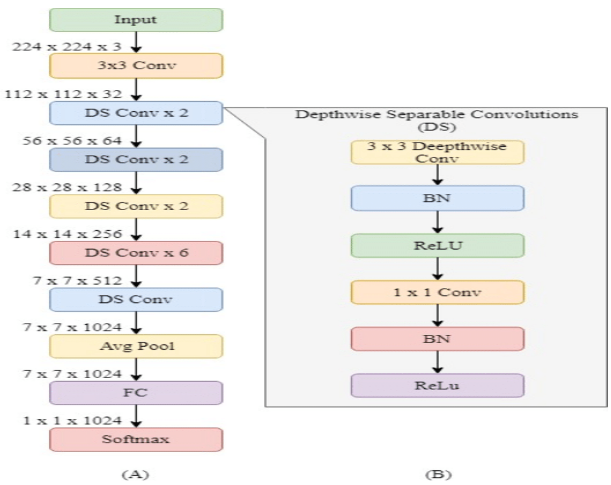

FIGURE 7: Architecture of MobileNet

IV.COCLUSION

The survey on smart handling of biomedical waste using a combination of deep learning, IoT, LoRa (Long Range), machine learning (ML), YOLO (You Only Look Once), and TensorFlow demonstrates a comprehensive and cutting-edge approach to addressing the challenges associated with biomedical waste management. The integration of these

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advanced technologies holds great promise in revolutionizing the efficiency, accuracy, and sustainability of biomedical waste handling processes.

The use of deep learning algorithms, particularly with frameworks like TensorFlow and YOLO, proves instrumental in automating the identification and classification of biomedical waste, ensuring proper segregation and disposal. This not only enhances the overall efficiency of waste management but also reduces the risk of human error.

The incorporation of IoT and LoRa technologies provides real-time monitoring capabilities, allowing for continuous data collection on waste generation, fill levels, and environmental conditions. This level of connectivity enhances the responsiveness of waste management systems, enabling timely interventions and optimizing resource utilization.

Machine learning further contributes to the adaptability of the system by continuously improving its ability to recognize and handle diverse biomedical waste categories. The iterative learning process ensures that the system becomes increasingly accurate over time, adapting to evolving waste streams and regulatory requirements.

The synergy between these technologies results in a holistic and intelligent biomedical waste management system, offering benefits such as increased regulatory compliance, minimized environmental impact, and improved safety for healthcare professionals and the community.

While the integration of these technologies presents a forward-thinking solution, it is essential to acknowledge challenges such as initial implementation costs, interoperability issues, and the need for ongoing training and education. Overcoming these challenges will be crucial for the widespread adoption and success of smart biomedical waste management solutions.

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