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Accuracy enhancement in mobile phone recycling process using machine learning technique and MEPH process

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ABSTRACT

The technological development, market expansion and increased population will lead the increased use of electronic equipment and production of e-waste worldwide. Disposal of electronic equipment is a challenging problem across the globe. Improper way of electronic waste disposal leads human health risk and environmental pollution. The report shows that 50,000 million tons of e-waste generated across the globe. Electronic waste includes CRT (Cathode Ray Tube), PCB (Printed Circuit Board), unused Television (TV), computers and mobile phones. In this paper we focus on recycling of unused mobile phones. The main objective of this research is introducing automation in metal purification measurement and improvement process using machine learning. The mobile phones contain different toxic metals such as cadmium, beryllium, lead and arsenic. Improper ways of unused mobile phone disposal contaminate water, air and soil. This research work has two parts. First part uses MEPH (Magnetic separation, Eddy current, Pyrometallurgical and Hydrometallurgical) process for metal separation, metal extraction and purification process. In the second part the purified metal is captured through camera and the captured image is subject to noise removal and given as input to the Convolutional Neural Network (CNN) classifier. The classification process is done in two ways; first one is taking input and classing the output. Second one is find the percentage of similarity to the particular class. We used the later one for finding the percentage of similarity between recycled metal and the pure metal. Suppose similarity is less than 90%, the purification process will be improved to enhance purity. In Machine learning different methods are available for feature extraction and classification among which we used the CNN. It easily find the spatial and temporal dependencies of input image by applying proper filters and also extracts high level features, dominant features using convolution and max pooling operation. This operation also reduces the computational power needed to process the input. Activation function plays important role in the feature extraction and classification process. In our research we used the ReLU (Rectified Linear Unit) function for validating the features learned from the input image. The most important advantage of using CNN is that it discovers the significant features without the human command. Also we used the image augmentation to increase the input image data set. The accuracy of metal classification measured using confusion matrix. From this research we got the purified metal and it is directly used for other product manufacturing.

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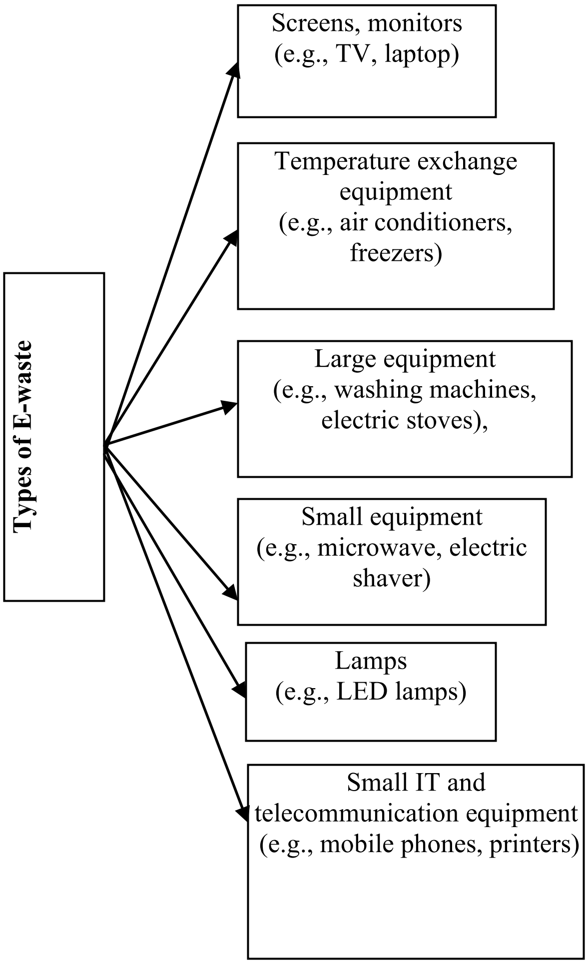

Fig. 1. Types of electronics waste.

1. Introduction

Technical innovation and sophistications in life increase the usage of electrical and electronic equipment's in day to day life. Now a day people under below average economy level have basic E- devices such as TV, Fridge, mobile phones. E-waste includes unused electrical and electronics equipment's.

Fig. 1 shows the types of Electronics and electrical waste. Informal way of disposing these waste create serious effects to environment and human being. The disposed mobile consist toxic metals such as lead (Pb), Beryllium (Be), Lithium (Li), Bromine (Br), Mercury (Hg), Arsenic (As), Barium (Ba), Cadmium (Cd).

Barium (Ba), lead (Pb), Mercury (Hg) and Arsenic (As) create brain damage, lung damage caused by Arsenic (As) and Beryllium (Be), blood disorder introduced by Barium (Ba) and Barium (Ba), fragile bones introduced by Cadmium (Cd), Kidney disorder caused by lead (Pb), Mercury (Hg) and Cadmium (Cd), heart and liver damage caused by Barium (Ba). EPA (Environmental Protection Agency) said that globally only 20% of waste is recycled and for 2020 Tokyo Olympic, the medal will be made from e-waste of 50,000 tones.

According to the report of Minerals Education Coalition, approximately 140 million cell phones are disposed per year. Prober recycling process will save human being from above mentioned damages. Recycling is the process of recovering useful product or material from waste. In this paper we give detailed explanation about recycling of waste mobile phones. E-waste generations measured by different methods such as market supply method, consumption and use method and saturated market method. Fig. 2 explains what the waste materials available in mobile phone are after disposal.

Abdelbasir et al. (2018) explained different recycling method used for printed circuit boards and they reviewed, a survey about e-waste management. They explained about the e-waste generation rate of Egypt and the impact of waste to people and environment. They also explained the Non-metallic components in e-waste, Biometallurgical processes, Pyrometallurgical processes, Hazardous substances present in the waste of printed circuit boards and Hydrometallurgical processes. Al-Thyabat et al. (2013) explained batteries recycling processes of LiBs and NiMH. They also gave a information

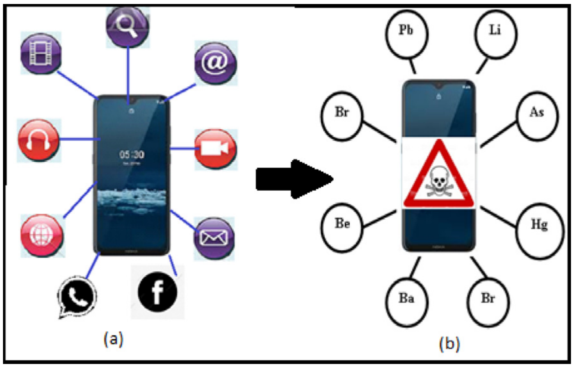

Fig. 2. (a) Before usage (b) After usage.

Table 1
Mass Composition of Metals for Mobile phone scrap (Hageluken, 2006).

Mass (%)					Mass (mg kg^{-1})		
Fe	Cu	Al	Pb	Ni	Ag	Au	Pd
5	13	1	0.3	0.1	1380	350	210

about Constituents of batteries, State of the art in battery recycling technology Physical based technologies, Chemical based technologies, Hydrometallurgical process, Drawbacks of recycling technologies and Mechanical treatment of batteries.

Diouf et al. (2015) explained the usage of recycled mobile phone batteries for a light emitting diode (LED) lamp and solar panel. The candles and kerosene lamps were replaced by LED lamp and solar panel. D'Adamo et al. (2016) explained some challenges in identify the profitability of the recovery process of waste EEE (Electrical and electronics equipment) and their printed circuit boards (PCB). They said that, in future the waste of EEE collected in three European Countries were related to economic indexes. They insisted that, in the revenue side, gold plays a vital role followed by copper and palladium. But the investment cost was very low for this recovery process of waste EEE. Habib et al. (2013) explained the separation methodology in which they separates the non-metallic and metallic fractions of PCBs using vertical vibration technology. They achieved 95% (measured through heavy liquid analysis) of metallic grades in recovered products. Under dry conditions high density and small sized complex particle of comminuted PCB particles were separated. They explained a new approach for dry, fine particle separation.

Li et al. (2017) explained the ECS (Eddy Current Separation) approach to separate PCBs (Printed Circuit Boards)from the plastic which were generated from compressed cell phones. With help of specific parameters in the computer simulation ECS was used to divide PCB from plastic. Magnetic roller rotating speeds, particle radius, feeding belt velocities were analyzed by design experts during the separation process. Lu and Xu (2016) reviewed current recycling technologies to separate precious metals from waste PCBs. They explained two step crushing and corona electrostatic separation methods to metals enrichment process for WPCBs". Hydrometallurgy + mechanical separation "technology achieve relatively high recovery rate of valuable metals, due to high economic cost and complexity this technology was not transferred to developing countries. Navazo et al. (2014) explained about the energy required to recover precious metals from discarded mobile phones. The recovery rate of palladium, silver, gold, copper, and nickel, lead, tin and antimony from the recycle processes described was 80 to 99%. Energy consumption to recover copper and gold from cell phones was half energy of that needed for gold and copper primary extraction. By reducing energy consumption they extract more resources.

Zazycki et al. (2017) explained the method using activated carbon and biopolymers to extract precious metals from waste electrical and electronics equipment (WEEE). Activated carbon (AC), chitosan (CTS) and chitin (CTN) was used as adsorbents to extract precious metals from mobile phone wastes. Thiourea leaching method was used to extract valuable methods. According to the equilibrium and kinetic viewpoints the adsorption of valuable metals was studied. Zhao et al. (2017) used liquid–solid fluidization technique to recover valuable metals from scrap mobile phones Printed Circuit Board (PCBs) particle.

The WPCB metal composition was chemically analyzed. A theoretical fluidization velocity was calculated for single components. Water velocity distribution and Particle shape factor was considered. WPCB particles appropriate operating velocity range was determined. Gu et al. (2019) analyzed the various technologies for recycle the waste mobile phones and also identify the limitations in that methods. Most of the PCBs recycling process have been developed to recover the valuable metals such as silver, gold, copper etc from waste mobile phones. Most recycling methods follow manual disassembly mechanism at a first step, so achievement of scalability impossible. Particle sizes used in industries were not suited for laboratories and it was not feasible economically. According to that analysis, primary target of mobile PCBs was gold and copper and the next target was cobalt and lithium that was extracted from WMP batteries.

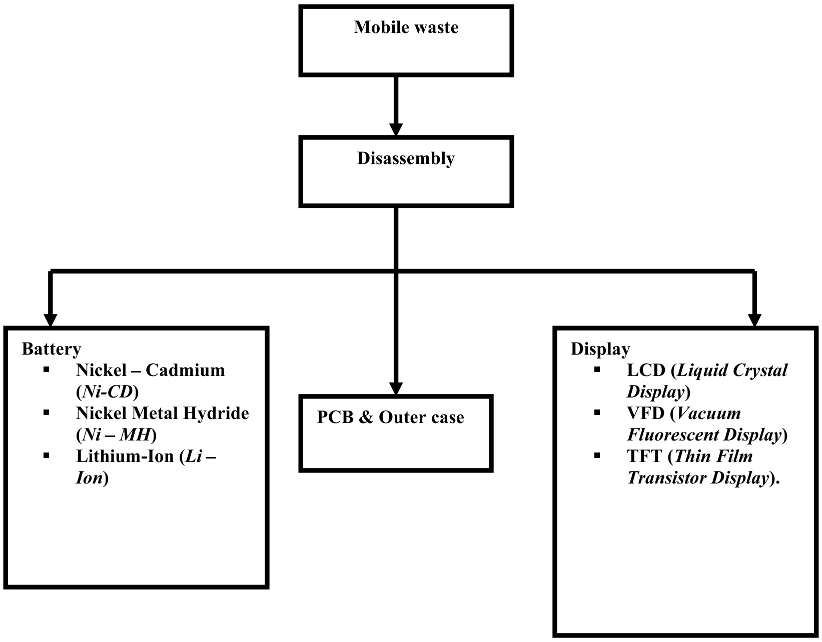

Fig. 3. Disassembly of mobile phone.

The major parts of waste mobiles are battery, PCB, display and outer case. Battery contains metals such as lead, mercury and cadmium. In general PCB contains cadmium and lead. There are more ways for treating e-waste such as land filling, incineration, reuse and recycling. Recycling of e-waste contains the following steps Disassembly, Upgrading and Refining. Table 1 shows the mass composition of mobile waste. Fig. 3 shows disassembly of mobile phone.

Kasper et al. (2011) explained about the methodology to extract the polymers present in the cell phones. Principal polymer types were identified from collected mobile phones and separated by their manufacturers/models. Electrostatic separation process was applied to recycle the Waste PCBs from that polymeric materials are identified. To fabricate the samples polymeric materials were mixed polymers of frames. It was evaluated by mechanical tests such as hardness test, tensile test and impact test.

Kim et al. (2011) explained about hydrometallurgical process to extract of gold from scrap mobile phone PCBs. In the recycling process they investigate electro-generated chlorine as oxidant and recovery was performed by ion exchange process. They used separate leaching reactors connected with anode container of a Cl2 gas generator. Copper leaching was increased with decrease in temperature and increase in concentration of acid. Kim et al. (2013) explained the novel approach for simultaneous extraction of precious metals from scrap mobile phones Printed Circuit Board (PCBs) and Automobile Catalysts. Without adding any metals or sub-products such as slime, dross and matte they perform honeycomb-type auto catalysts and extract the precious metals. Using that approach 95% of precious metals were extracted from scrap mobile phone PCBs.

Yin et al. (2014a) investigate the consumer behavior towards scrap mobile phone recycling in China. Survey was performed in the country to explore consumer's attitude behaviors and willingness for recycling of scrap mobile phones. The survey was analyzed with multinomial logistic regression analysis method. The results showed that the actual life of cell phones in China is generally lesser than three years. Petter et al. (2015) and Yin et al. (2014b) compared various leaching processes of copper and gold from PCBs of scrap mobile phones. They analyzed sulfuric acid–hydrogen peroxide and iodine (SAHPI) nitric acid and thiourea (NT) process to extract the gold and copper from the scrap mobile phones. They achieved very high recovery rate for copper and gold. Environmental process was involved in iodine leaching.

Yushkova and Feng (2017) done a analysis among the china and Germany university students to identify which determinants influenced to bring waste mobile phones for recycling purpose. They examined the indirect and direct effects of environmental benefits of reuse and pro-environmental attitude of recycle mobile phones. They took knowledge, social norms and intention as a key factor. Among those factors they found which one was more influenced to bring their waste mobile phones to recycle process.

Findings from literature survey

The above mentioned reviews only explained about pros and cons of the metal separation, metal extraction and metal purification process. Now a day's machine learning plays major role in all part of our life especially in medical field

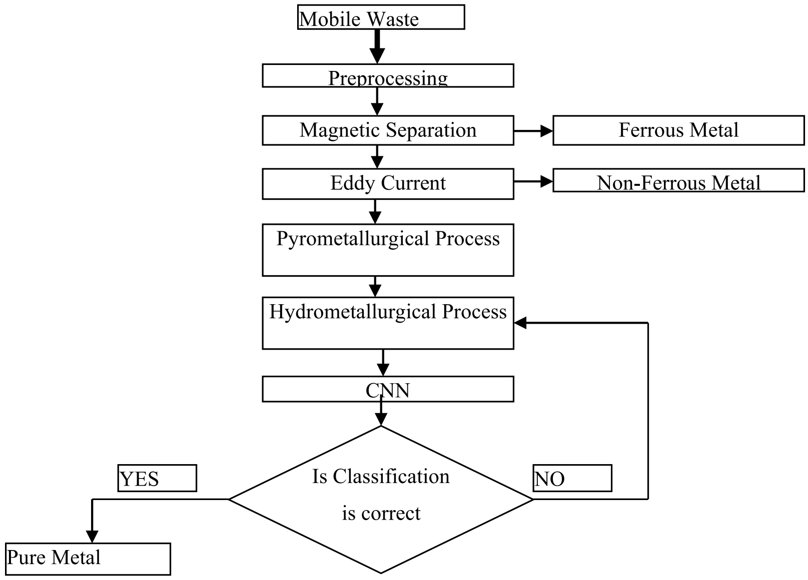

Fig. 4. Flow diagram.

image classification done by machine learning and deep learning algorithm. Senthil Selvi and Sukumar (2019), Thaha et al. (2019) used machine learning for brain tumor segmentation. Renith and Senthilselvi (2020) done diabetic retinopathy classification using machine learning. Surya and Senthilselvi (2020) used machine learning algorithm for food adulteration detection. As a computer engineer we have an idea to use machine and deep learning algorithm to measure a purity of the metal extracted. No one concentrates on the purity enhancement process. Recyclers use different devices to measure the quality of the recycled metal. But we proposed a new method for purity measurement and enhancement based on image classification using machine learning method. Here we took a image of recycled metal and extracted features from it and compared with the features of pure metal then we find the probability of similarity. Based on the similarity value the further process will be taken place. The similarity value is less than the threshold value, then the metal again going for purification process. In this paper we are concentrating on accuracy enhancement by finding similarity between pure metal and recycled metal.

Remaining section of the paper organized as follows, Section 2 explains proposed method, and Section 3 explains conclusion and future work.

2. Proposed method

This section briefly explains about the proposed method. It includes detailed explanation about metal separation, metal extraction, metal purification and step by step process of feature extraction and classification process in Convolutional neural network. The proposed method has two parts; first part explains metal extraction and purification process. Second part explains accuracy measurement and enhancement process using CNN.

Steps in proposed method

The proposed method consists of six steps. First three steps explain about metal separation, extraction and purification. The metal separation is done by magnetic separation and eddy current method. Metal extraction and purification is done by pyrometallurgical and hydrometallurgical process. Fig. 4 shows the flow diagram of proposed method. Fig. 5 shows the sub process of step 1, 2, 3.

Step.1 Preprocessing
Step.2 Material separation
Step.3 Material Extraction and purification
Step.4 Extracted materials captured by the camera.
Step.5 The captured image given as input to CNN
Step.6 CNN process the pixels and determines the purity of material extracted by the features which most correlates to the dataset (Pure metals)

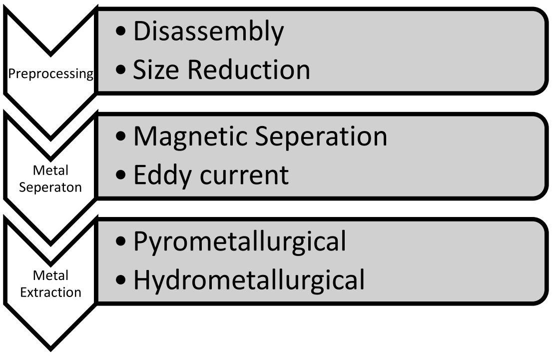

Fig. 5. Sub process of Step 1, 2, 3.

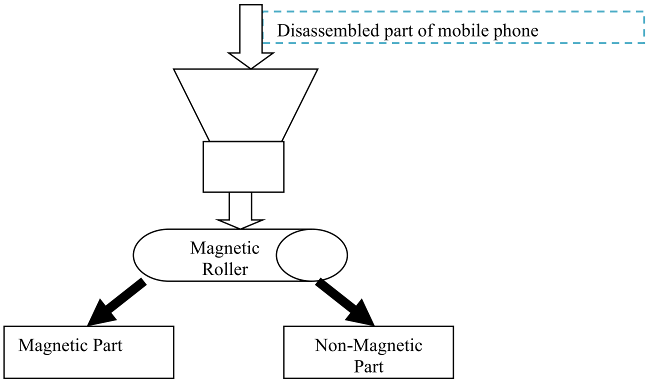

Fig. 6. Concept of magnetic separation.

2.1. Metal extraction and purification process

2.1.1. Magnetic separation

Magnetic separation is the first step of mobile waste recycling process. In this method magnetic waste is separated from nonmagnetic waste. Using this method, from the dissembled part of mobile phone magnetic material is separated. In this method magnetic roller is used for magnetic separation.

Every mobile phone has a small Neodymium (NdFeB) magnet. It is used for camera auto focus, vibration mode, speaker and receiver in mobile. Approximately mobile phone consists of 14 small NdFeB magnets.

Fig. 6 shows the concept of magnetic separation.

2.1.2. Eddy current separation

Eddy current separation is the second step of mobile waste recycling process. The Non-magnetic output from magnetic separation is given as an input to eddy current separation method. It uses heavy magnetic field to separate non-ferrous metals from metals. To make effective separation this method uses eddy current. The mobile phone is made by different metals. Phone cases made by light weight metal, the wiring of the phone contains copper, silver and gold. The circuits are made by tungsten and platinum. The battery is made by lithium and carbon. Fig. 7 explains eddy current separation process. In this method approximately 90% of the non ferrous metals separated from the input. The size of non-ferrous metals varies from 5 mm to 350 mm.

2.1.3. Pyrometallurgical and hydrometallurgical process

In Hydrometallurgical process aqueous solutions is used to extract metals from ores on the other hand pyrometallurgical process uses high temperature for metal extraction. Pyrometallurgical process involves smelting, roasting and refining. Magnetic separation and eddy current method separate the ferrous and nonferrous metal from the waste. The remaining metal available with waste is Cu, Pb, silver and gold hence the output from eddy current separation given to smelter which accepts Cu and Pb scrap. In Pyrometallurgical process Cu and Pb scrap is given as input to furnace, the metals are collected from the molten path and oxides collected from slag phase. Ceramic parts in input feed increase the generated volume of slag in blast furnaces, which in turn increase the risk of losing PMs (Au, Ag and Pd) from BMs (Cu, Pb and Zn). The recovery and purity process further improved by hydrometallurgical method.

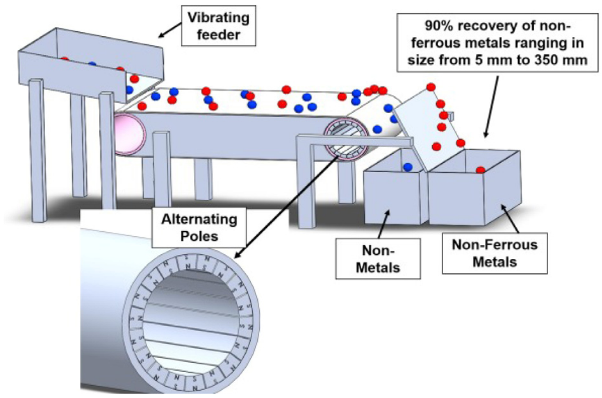

Fig. 7. Concept of eddy current separation (Smith et al., 2019).

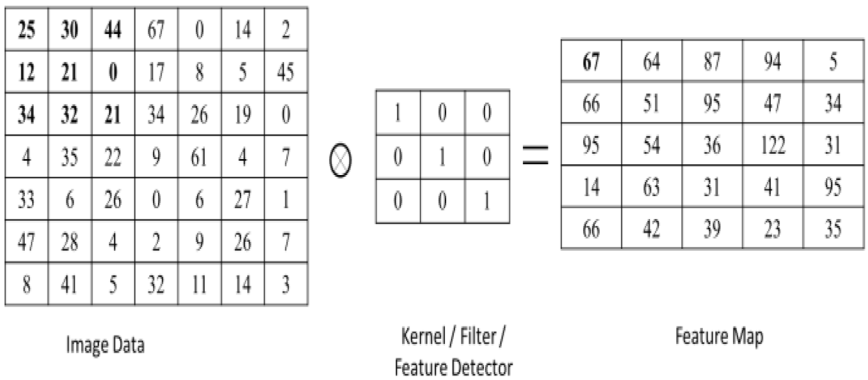

Fig. 8. Example of convolution operation.

2.2. *Accuracy measurement and enhancement*

2.2.1. *Steps in convolutional neural network (CNN)*

Step.1 The work Initiated with an input image
Step.2 Feature map is created after applying different filters
Step.3 Non-linearity is increased by ReLU function
Step.4 Pooling layer reduce the dimensionality
Step.5 Pooled images converted into one long vector.
Step.6 Long vector is given to the fully connected layer.
Step.7 The network processes the features. The fully connected layer determine the class of the input image
Step.8 The training process done through back propagation and forward propagation for, several epochs. This process is repeated until get a precise neural network.

2.2.2. *Working of convolutional neural network*

The output of hydrometallurgical process is captured by the camera. The captured image is restored using filter before feed to CNN. Senthilselvi et al. (2020), Selvi et al. (2020) used different filters for remove salt and pepper noise from image (Senthil Selvi and Sukumar, 2019). In the proposed system CNN works with three layers. First Layer is Convolutional Layer. It extracts useful information from the image. Array of pixel values given as input to this layer then the pixel values are multiplied with filter values and multiplication is summed. This procedure is repeated for entire image. ReLU is applied after convolution. The negative pixel values are replaced by zero in ReLU operation.

Second layer is pooling layer. Pooling is otherwise called sub sampling and down sampling. The output from the convolution layer is given as input to this layer. Different types of pooling are there among which max pooling is used. In this layer dimensionality reduction taken place without affecting the image features. Fig. 8 shows example of convolution operation.

Third Layer is Fully-connected Layer. The output of max pooling is given as input to this layer. It matches test data feature with the trained data feature. In this layer all the nodes are connected to adjacent layer nodes. The classification

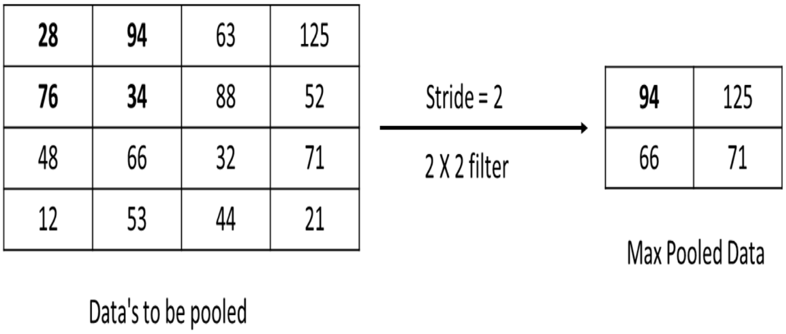

Fig. 9. Sample pooling operation.

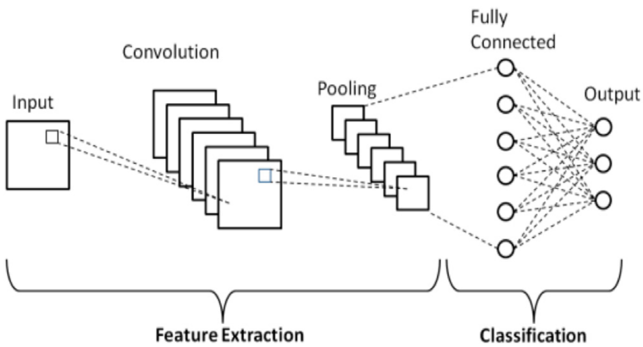

Fig. 10. Complete CNN architecture.

score was calculated in this layer. Using this classification we measure the purity of the metal extracted. Fig. 9 shows sample pooling operation. Fig. 10 shows complete CNN architecture.

2.2.3. Accuracy measurement

Different parameters are available to measure the performance of the machine learning system. In our research we measure the accuracy of the classification system by confusion matrix. Fig. 11 shows the confusion matrix. The predicted value come under the category of true, false, positive and negative. Eq. (1) shows the formula for calculating accuracy.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})} \tag{1}$$

2.2.4. Explanation to confusion matrix

This section explains about technical terms involved in the confusion matrix using an example, in which we took sample aim as classify the extracted metal is lead.

True Positive:

True positive means our prediction is positive and also it is true.
Example: prediction is lead, it is true

True Negative:

True negative means our prediction is negative and it is true
Example: prediction is extracted metal is not gold, it is true

False Positive:

False negative means our prediction is positive, it is false
Example: prediction is extracted metal is gold, it is false

False Negative:

False negative means our prediction is negative, it is false
Example: prediction is extracted metal is not lead, it is false

	Class1(Positive) Predicted	Class2(Negative) Predicted
Class1(True) Actual	True Positive	True Negative
Class2(False) Actual	False Positive	False Negative

Fig. 11. Confusion matrix.

2.2.5. Sample accuracy calculation

- Number of samples = 200
- True Positive = 145
- True Positive = 20
- False Positive = 15
- False Negative = 20

$$\text{Accuracy} = \frac{(145 + 20)}{(145 + 15 + 20 + 20)}$$
$$\text{Accuracy} = \frac{(165)}{(200)}$$
$$\text{Accuracy} = 0.825$$

3. Conclusion and future work

The increase in the population and short life span of mobile phone increase the mobile waste tremendously. The landfill of mobile waste creates injurious effect to both human being and environment. Many devices are available to measure the purity of the metal. As a computer engineer we proposed the new method to measure and improve the purity of the recycled metal using Convolutional Neural Network. The main aim of this paper is to improve the accuracy of metal extraction and purification process based on the value of probability of similarity. The image database is divided to testing image and training image. The CNN is trained using pure metal image. The testing is done by captured image. In this paper material separation is done by magnetic separation and Eddy current technique. Metal extraction and purification is done by Pyrometallurgical and hydrometallurgical process. The accuracy of the system is measured by confusion matrix. In metal separation ferrous and nonferrous metals were separated. The primary metal extracted from Mobile PCB is gold and copper and battery is cobalt and lithium. At the end of this research we obtain the pure metal which is directly used for other product manufacturing. It is a automated process by which the photo of the recycled metal is captured by robot and feed it to the CNN classifier. As a result the Manual intervention is avoided and the purity is calculated and improved in the recycled field itself. In future the accuracy will be improved by some other machine learning network or hybrid two or more machine learning network.

CRediT authorship contribution statement

A. Senthilselvi: Conceptualization, Methodology, Software, Data curation, Writing - original draft, Writing - review & editing, Validation. **V. Sellam:** Methodology, Software, Data curation, Writing - review & editing. **Saad Ali Alahmari:** Methodology, Validation, Writing - review & editing, Validation. **Sivaram Rajeyyagari:** Writing - review & editing, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abdelbasir, S.M., Hassan, S.S.M., Kamel, A.H., El-Nasr, R.S., 2018. Status of electronic waste recycling techniques: a review. Environ. Sci. Pollut. Res. 25 (17), 16533–16547.

Al-Thyabat, S., Nakamura, T., Shibata, E., Iizuka, A., 2013. Adaptation of minerals processing operations for lithium-ion (LiBs) and nickel metal hydride (NiMH) batteries recycling: critical review. Miner. Eng. 4–17.

D'Adamo, I., Rosa, P., Terzi, S., 2016. Challenges in waste electrical and electronic equipment management: a profitability assessment in three European countries. Sustainability 8 (7), 633–641.

Diouf, B., Pode, R., Osei, R., 2015. Recycling mobile phone batteries for lighting. Renew. Energy 78, 509–515.

Gu, F., Summers, P.A., Hall, P., 2019. Recovering materials from waste mobile phones: Recent technological developments. J. Cleaner Prod. 1, 1–19.

Habib, M., Miles, N.J., Hall, P., 2013. Recovering metallic fractions from waste electrical and electronic equipment by a novel vibration system. Waste Manage. 33 (3), 722–729.

Hageluken, C., 2006. Improving metal returns and eco-efficiency in electronics recycling-a holistic approach for interface optimisation between pre-processing and integrated metals smelting and refining. In: IEEE Proceedings of the International Symposium on Electronics and the Environment, pp. 218–223.

Kasper, A.C., Bernardes, A.M., Veit, H.M., 2011. Characterization and recovery of polymers from mobile phone scrap. Waste Manag. Res. 29 (7), 714–726.

Kim, E., Kim, M., Lee, J., Pandey, B.D., 2011. Selective recovery of gold from waste mobile phone PCBs by hydrometallurgical process. J. Hazard. Mater. 198, 206–215.

Kim, B.S., Lee, J.C., Jeong, J., Yang, D.H., Shin, D., Lee, K.I., 2013. A novel process for extracting precious metals from spent mobile phone PCBs and automobile catalysts. Mater. Trans. 54 (6), 1045–1048.

Li, J., Jiang, Y., Xu, Z., 2017. Eddy current separation technology for recycling printed circuit boards from crushed cell phones. J. Cleaner Prod. 141, 1316–1323.

Lu, Y., Xu, Z., 2016. Precious metals recovery from waste printed circuit boards: a review for current status and perspective. Resour. Conserv. Recy. 113, 28–39.

Navazo, J.M.V., Méndez, G.V., Peiró, L.T., 2014. Material flow analysis and energy requirements of mobile phone material recovery processes. Int. J. Life Cycle Assess. 19 (3), 567–579.

Petter, P.M.H., Veit, H.M., Bernardes, A.M., 2015. Leaching of gold and silver from printed circuit board of mobile phones. Rem: Revista Escola Minas 68 (1), 61–68.

Renith, G., Senthilselvi, A., 2020. Accuracy Improvement in Diabetic Retinopathy Detection using DLIA. J. Adv. Res. Dyn. Control Syst. 12 (7), 133–149.

Selvi, A.S., Kumar, K.P.M., Dhanasekeran, S., Maheswari, P.U., Ramesh, S., Pandi, S.S., 2020. De-noising of images from salt and pepper noise using hybrid filter, fuzzy logic noise detector and genetic optimization algorithm (HFGOA). Multimedia Tools Appl. 79 (5), 4115–4131.

Senthil Selvi, A., Sukumar, R., 2019. Removal of salt and pepper noise from images using hybrid filter (HF) and fuzzy logic noise detector (FLND). Concurr. Comput.: Pract. Exper. 31 (12), 1–4501.

Senthilselvi, A., Sukumar, R., Senthilpandi, S., 2020. Hybrid fuzzy logic and gravitational search algorithm-based multiple filters for image restoration. Int. J. Data Anal. Tech. Strateg. 12 (1), 76–97.

Smith, Y.R., Nagel, J.R., Rajamani, R.K., 2019. Eddy current separation for recovery of non-ferrous metallic particles: A comprehensive review. Miner. Eng. 133, 149–159.

Surya, V., Senthilselvi, A., 2020. A qualitative analysis of the machine learning methods in food adultery: A focus on milk adulteration detection. J. Adv. Res. Dyn. Control Syst. 12 (4), 543–551.

Thaha, M.M., Kumar, K.P.M., Murugan, B.S., Dhanasekeran, S., Vijayakarthick, P., Selvi, A.S., 2019. Brain tumor segmentation using convolutional neural networks in MRI images. J. Med. Syst. 43 (9), 1–294.

Yin, J., Gao, Y., Xu, H., 2014a. Survey and analysis of consumers' behaviour of waste mobile phone recycling in China. J. Cleaner Prod. 65, 517–525.

Yin, J., Zhan, S., Xu, H., 2014b. Comparison of leaching processes of gold and copper from printed circuit boards of waste mobile phone. Adv. Mater. Res. 274, 3–2746.

Yushkova, E., Feng, Y., 2017. What explains the intention to bring mobile phones for recycling? a study on university students in China and Germany. Int. J. Energy Econ. Policy 14 (3), 501–516.

Zazycki, M.A., Tanabe, E.H., Bertuol, D.A., Dotto, G.L., 2017. Adsorption of valuable metals from leachates of mobile phone wastes using biopolymers and activated carbon. J. Environ. Manag. 188, 18–25.

Zhao, C., Zhang, X., Ding, J., Zhu, Y., 2017. Study on recovery of valuable metals from waste mobile phone PCB particles using liquid–solid fluidization technique. Chem. Eng. J. 311, 217–226.

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