



Biomedical Waste Sorting & Classification Using Deep Learning

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Declaration

I hereby declare that this dissertation to the best of my knowledge, is solely composed by myself and it neither contains any direct or indirect materials from previously published articles nor written by another person. Further, this thesis has not been submitted for any award or degree of any other university or institute of higher education except as specified.

Certified by



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Date : 28th August 2021

The above candidate has carried out research for the M.Sc. thesis under my supervision.

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Abstract

Biomedical wastes (BMWs) include potentially infectious, sharps, pharmaceuticals and radioactive wastes probably generated by hospitals, vaccination centers, biomedical laboratories, etc. Handling and disposal of biomedical wastes potentially have multiple risk factors. Currently, hospitals and laboratories use color-coded bins to classify and categorize different types of wastes to ease the handling and the disposal process. Sometimes due to human errors these wastes could be miscategorized or misplaced in different bins. In recycling terms this is known as waste contamination. Contaminating the biomedical waste streams causes a huge potential threat to the people who handle them.

Computer vision based biomedical waste classification is one of the best ways to prevent these issues. But applying pure computer vision algorithms is much more suitable for small tasks such as pattern recognition, edge detection etc. In order to classify different kinds of biomedical wastes, then convolutional neural networks (CNN) would be a much more suitable choice. This research proposes a deep learning model which accurately classifies several selected biomedical wastes such as syringes, blades and sample collection tubes with a prediction accuracy around 96% on the test dataset. Further the implemented model approximately localizes the biomedical wastes to serve robotics and smart-bin applications.

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Abbreviations

WHO	World Health Organization
UNICEF	United Nations Children's Fund
HBV	Hepatitis B Virus
HCV	Hepatitis C Virus
HIV	Human Immunodeficiency Virus
POP	Persistent Organic Pollutants
MRI	Magnetic Resonance Imaging
DL	Deep Learning
AI	Artificial Intelligence
NLP	Natural Language Processing
DNN	Deep Neural Network
CNN	Convolutional Neural Network
OSS	Open Source Software
IEEE	Institute of Electrical and Electronic Engineers
ML	Machine Learning
CV	Computer Vision
ANN	Artificial Neural Network
RNN	Recurrent Neural Network
FFNN	Feed Forward Neural Network
CPU	Central Processing Unit
GPU	Graphics Processing Unit
TPU	Tensor Processing Unit
FCNN	Fully Connected Neural Network

VGG	Visual Geometry Group
ReLU	Rectified Linear Unit
ROI	Region Of Interest
BN	Batch Normalization
PCA	Principal Component Analysis
L1-PCA	L1-Norm Principal Component Analysis
CED	Canny Edge Detection
PHT	Probabilistic Hough Transformation
HLT	Hough Line Transformation
RAM	Random Access Memory
CUDA	Compute Unified Device Architecture
Grad-CAM	Gradient - Class Activation Map
URL	Uniform Resource Locator
CC	Cubic Centimeter
RPI	Raspberry Pi
IOT	Internet Of Things