PREDICTION OF BURR FORMATION IN END MICRO MILLING Poly methyl Methacrylate (PMMA) AND Polycarbonate (PC) SUBSTRATES USING CONVOLUTIONAL NEURAL NETWORK (CNN)

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Abstract. Polymer microfluidic device is growing in the fields of disease detection, drug synthesis, and environmental monitoring because of the benefits of the miniaturized platforms that provides rapid high-throughput analysis at small sample volumes. A machining technique called micro milling is employed in the manufacture of micro components (micro fluidic devices) such as poly methyl methacrylate (PMMA) or polycarbonate (PC). Micro milling has the advantage of being a quicker, more affordable, and more effective method for fabricating more complex structures. PMMA has been used as the substrate in this study for micro milling followed by factor analysis. This aim of this study is to understand the influence of each micro milling parameter to the surface quality. This paper includes 450 microscopic images of the micro-milling substrate by different parameters like spindle speed, depth of cut and Surface quality. The microscopic images are divided to test, train and Val dataset, using three datasets and a Convolutional Neural Network (CNN) is designed.

1 Introduction

Nowadays automation, machine learning, security, and other advancements, in technology are expanding across all pro- professions. Many industries are developing automation to lessen human effort and error. Micro milling has become one of the advanced technologies where it is used to cut materials into small parts i.e (micrometres or Milli meters) and complex structures into small parts. This technology is mainly used in electric fields, aerospace, medical, biomedical etc. High precision, low cost, and three-dimensional cutting capability are the ad- vantages of micro milling. Computer numerical Control (CNC) is the modern milling machine that does the work automatically by reducing repeatability and precision, by reducing human effort/error with advanced capabilities. CNC can remove a part of a piece from a three-dimensional material/structure. Milling is used to removing of metal from a workpiece using a machine tool which has several points with its rotating axis [1]. Fig 1 shows a computerised cutting system (CNC) in action as it precisely forms metal or other materials with the desired depth, speed, and diameter.

Burr refers to the ridge formation on metal. A toolbox called a microfluidic lab- on-chip (LOC) is used in research and chemistry to control small fluidic volumes. It provides disposable devices with high throughput, a short turnaround time, and minimal usage. Moulds are the foundation of polymeric LOC. Depending on their construction, moulds can shrink to a size between 20 and 50 micrometres during the manufacturing process. This study examines the accuracy and precision of milling polymeric materials using convolution neural

Fig. 1. Computer Numerical Control (CNC)

networks. Due to its low cost and high volume manufacturing technique, plastic (PMMA/PC) was chosen as the substance in this experiment for investigation. After cutting the PMMA/PC substrate, a rough layer formed at the substrate's edge, as shown in Fig. 2. Called burr formation. Below shown image is the microscopic image. All the microscopic images has been collected and the images has been divided into train and test dataset then CNN network model has been build.

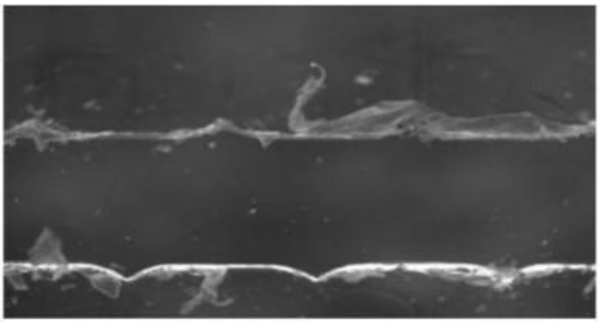

Fig. 2. Microscopic Image of Burr

Performed 450 slot milling (size of slot 9*3 mm) experiments using micro milling process by changing micro milling parameters like spindle speed, feed rate and depth ofcut. From these experiments, I understood how surface quality (Burr) varies by changing experimental parameters.After performing experiments, took a microscopic Image ofeach experiment using a stereomicroscope. Divided 450 microscopic images into 300 Images as training data set and 150 images as testing data set Created convolutional neuralnetwork (CNN) for the task of burr identification which is trained by training data set and tested by testing data set.

The rest of the paper is organized in the following manner. Section 2 includes literature review. Section 3 Micro milling Section 4 Techniques for image classification Section 5 Proposed Network Section 6 Resent Architecture Section 7 Experimental Results Section 8 Conclusion and future work.

2 LITERATURE REVIEW

Manufacturing of metals, polymers, ceramics, and other materials has become the main application for mechanical micro-milling [1]. Ingo G. Reichenbach has authored the most insightful work on micro-milling PMMA. The method of micro milling PMMA employing tool diameter D 50µm on a 3µm axis milling machine isthe major topic of this research. The paper is based on thecreation of microfluidic structures with three burrs on topand 60 mu on the bottom [2]. Different techniques, including micro-milling, hot embossing, injection modelling, etc., can be used to fabricate plastic [3]. A burr, also known as a rough edge is formed after cutting metal or plastic which is removed with a deburring tool. Burr shape comes in three different forms i.e. saw-type, burr-breakage, and knife-breakage [4]. Initiation, development, and formation make up the three aspects of the formation. On commercial plasticine, an orthogonal machine is used to remove the burr that has formed on theplastic [5]. Li Chen et al. [6] evaluated the real-world handwritten character database for CNN and Deep Belief Network (DBN). In comparison to DBN, CNN’s classification accuracy rate achieves the best results. CNN’s accuracy is 92.91 per cent, while DBN’s is 91.66 per cent. Image categorization in machine learning can be carried out using SVM, decision trees, K-Nearest Neighbor, CNN, etc. The best results for picture classification come from comparing CNN to all other networks. Convolutional neural network is employed for visual imagination. Some applications of CNN include image identification, audio recognition, text classification and so on [7].Multi input convolutional neural network hasbeen designed for new dataset of flower garden .On performing analysis with single input CNN the accuracy is 89.6 percent but the multi input CNN is increased by 5 percent average[8].

Yann le Cunn et al [9] introduced deep learning and itsalgorithms in detail. Convolutional neural networks,recurrent neural networks, and backpropagation using multilayer perceptrons are only a few of the techniques thatare thoroughly covered with examples. The potential of unsupervised learning in artificial intelligence has also beendiscussed. Norhidayu Binti Abdul Hamid et al [10] used Support vector machines (SVM), K- Nearest Neighbor(KNN), and convolutional neural networks to evaluate the performance of MNIST datasets. The Multilayer Perceptron didn’t work effectively on that platform since it couldn’t reliably distinguish the digits 9 and 6 and reach the global minimum before being trapped in the local optimal. Other classifiers performed correctly, and it was determined that by using the model on the Keras platform, CNN performance might get enhanced. Convolutinal Neuralnetwork has number of advantages compared to other techniques in image recognition Samer Hizaji has discussed about the basis of CNN and the various layers used with the traffic sign recognition example [11].for this example implementation software has been developed using cadence virtusa tool can trade off computational burden and energy for a modest degradation in sign recognition rates. In recent times, there has been a notable proliferation of image recognition methodologies, with a particular emphasis on harnessing the power of deep learning. These approaches have exhibited remarkable advancements compared to earlier techniques, especially in the realm of general object recognition competitions. For instance, Hironobu Fujiyoshi[12] highlighted the crucial significance of deep learning in image recognition and also delved into the latest trends in the application of deep learning in autonomous driving. Furthermore, S.H. Lee introduced a method for predicting burr formation during face milling, employing a combination of artificial intelligence and the optimized Taguchi method [13]. In this context, an artificial neural network (ANN) was meticulously constructed for machining aluminum alloy 6061-T6, leading to enhanced outcomes.

Anwar Hossain's research delved into the creation of a CNN network model using the CIFAR-10 dataset. Additionally, the paper discussed the implementation of this model with CPU training, emphasizing reduced training times through the use of MAT Convert.[14] Koichi Ito proposed a method for predicting age and gender from facial images, leveraging a convolutional neural network (CNN). The dataset utilized in this study, the IMDB-WIKI dataset, contained pertinent information such as acquisition data, date of birth (DOB), gender, and face detector scores. Regression techniques were employed for age estimation, while classification methods were used for gender prediction [15]. Furthermore, Haritha introduced a transfer learning model using Googlenet for the prediction of COVID-19 from chest X-ray images, employing a CNN architecture named Inception V1. The results of this study demonstrated the efficacy of transfer learning models in disease prediction, with a training accuracy of 99% and a testing accuracy of 98.5%.[16].

3 Micro milling

According to David J Guckenberger, plastic is the most common choice among various microfluidics because of itscharacteristics. Plastic is produced at a low cost and in large quantities. Fabrication is the process of making something from scratch like Metal Fabrication, Etymology of Fabrication. Fabrication of Plastic can be done using different methods of fabrication like micro milling, stereolithography, hot em- bossing, injection moulding, etc. Eachof them has its own advantages and limitations but when itcomes to micro milling it has a unique advantage towards ultra-rapid prototyping as it is low cost and possess high resolution and versatility regarding material choices. In theabove-mentioned fabrication methods, hot embossing and injection moulding are indirect methods as they cut the material into parts using moulds. Micro milling and StereoLithography are the other two fabrication processes which perform by using direct methods without making use of moulds. The fabrication method is chosen based on some properties like technical comparison, cost comparison and quality comparison. In this study, we have taken a Convolutional neural network to perform the analysis withaccuracy, precision and recall. As we collect the images ofthe material after the fabrication process, CNN is used to check the accuracy of the outputs.

4 Techniques for Image Classification

There are several methods for classifying images in ma- chine learning viz. Support Vector Machine (SVM), K- Nearest Neighbor (KNN), and Convolutional Neural Network(CNN)[17].

4.1 Support Vector Machine (SVM)

A supervised learning approach called Support Vector Ma- chine (SVM) is applied to classification and regression issues. The boundary that SVM establishes divides n-dimensional space into classes that are separated by a hyperplane. SVM’s primary benefit is its ability to use the kernel to do a non-linear classification.

4.2 K-Nearest Neighbour (KNN)

The simplest algorithm used in supervised learning approaches is K-Nearest Neighbour (KNN). KNN algorithmdoes not make any assumptions about the data when fresh data is added. KNN is a non-parametric algorithm, where itcompares new data to stored/available data for similarity before making any assumptions and places the new data inthe category that is the most comparable. Consequently, theKNN technique is also known as the Lazy Algorithm.

4.3 Convolutional Neural Network (CNN)

According to Szegedy [18], a deep neural network is an artificial neural network (ANN) with many layers. An ANN component known as the convolutional neural network is primarily utilized for visual imagination. In CNN, there are three layers: the hidden layer, the input layer, and the output layer [1,9]. The hidden layer is made up of numerous convolutional layers that are combined viamultiplication or the dot product. The image of convolutional neural network is shown in Fig. 3. The inputlayer, hidden layer, and output layer are all visible in the image.

CNN is frequently used to resolve both complex and straightforward image recognition patterns. Every layer inCNN will have a relationship between the input image andthe final class score.

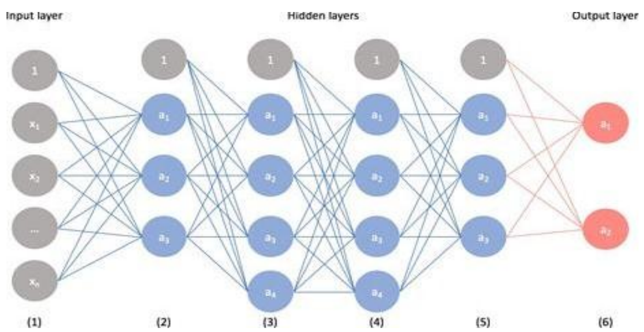

Figure 3. Convolutional Neural Network

CNN is mostly used for image pattern recognition; it breaks/encodes the image into a structure and reduces the parameters needed to set up the model, which is the fundamental difference between CNN and the standard ANN. Traditional ANN, on the other hand, frequently hasdifficulty handling the computational complexity needed to compute image data. CNN is utilized in this study to forecast the accuracy of image recognition

5 Proposed Network

For this experiment, a convolutional neural network hasbeen suggested. A total of 450 microscopic images have been collected and submitted as input, of which 150 photoshave been utilized for testing and 300 images have beenused for training. As discussed earlier, the convolutional neural network has three layers namely input, hidden, andoutput. The hidden layer includes the pooling layer, convolutional layer, ReLU layer, fully linked layer, loss layer, and other layers. When the operations are different for each layer, the input layer uses the width and height of the input image, spanning the channels where it stores theraw pixel data. CNN architecture has been separated intoclassification and feature extraction as indicated in Fig. 4.The feature extraction process includes the input layer, convolution layer, and pooling layer. While the output layerand fully connected layer fall under classification. Betweenthe convolution layer and the pooling layer, residual neural network (ResNet) processing takes place. The Convolutional Layer is the foundation of CNN architecture. A group of learnable filters with narrow fields that extendto a deep input volume make up this layers' parameter. Byperforming the dot product between each filters' entries during forward passing, each filter convexly crossed the width and height of the input volume creating a 2- dimensional (2D) map of the filter's activation. The entireoutput volume of the convolution layer is formed by the filters' activation map. The neurons' output will be represented by each entry in the output volume. A neuronis a tiny area of the input.

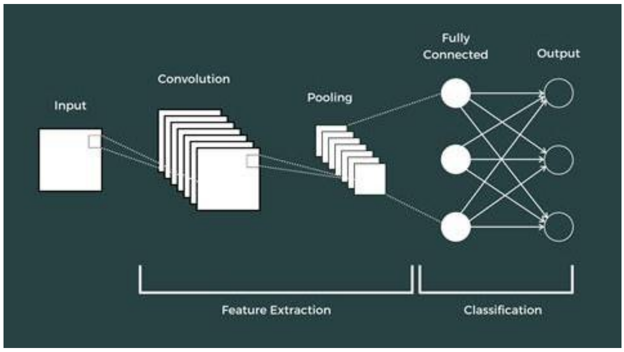

Fig. 4. CNN-architecture

5.1 Pooling Layer

CNN uses a non-linear down-sampling technique calledthe pooling layer. There are several ways to create pooling,but max pooling is the one that is most frequently employed.The input image is separated into a collection of non- overlapping rectangles in this layer, with each region receiving the greatest output possible. After every two convolution layers, pooling is added. Every slice or regionof depth is separately operated on by the pooling layer, which also changes its spatial size. 75 per cent of the activation is removed by applying a pooling layer with filters of the 2x2 size as illustrated in Fig. 5 at every depth size and it is given in (1). As shown in Fig 5 the input is size of 4x 4 which has further divided into four non-overlapping 2x2 matrix sizes.

$$f_{(x,y)}(S) = max_{(a,b=0)} S_{(2x)+(a,2y+b)} \qquad (1)$$

Activation Function: Based on the threshold limit, a mathematical function converts the input to the desired output. When output surpasses the threshold limit, these cause the neuron to become active.

5.2 Rectified Linear Unit Layer (ReLu)

Rectified Linear Unit Layer is a non-linear function thatwill produce a positive or a negative result depending on the input value f(x) given in (2).

$$f(x)= max(0,x) \qquad (2)$$

Without changing the receptive fields of the convolutionlayer, it makes the decision function and the entire networkmore nonlinear.

5.3 Fully Connected Layer

After maximum pooling, the entire connected layer is used for high-level reasoning. Each neuron is connected using a fully connected layer when moving from one layerto another. The typical multi-layer perceptron neural network is equivalent to this one. In each layer neuron receives input from the previous layer from different locations of the layer. Each single neuron in fully connected layer receives input from everyelement of the previous layer whereas in convolutional layer the first layer of the CNN network receives input only from the restricted subarea (size of the subarea is 5x5) which is of in square shape. This input process of neuron form previous layer to the current layer is known as the receptive field. In fully connected layer the receptive area is the entire area of previous layer. Convolution layer the receptive field is smaller than the previous layer. In receptive field the subarea of original input image will be increasingly growing as getting deeper into the architecturedue to repeating process of convolution which takes into the account the value of a specific pixel.

5.4 Loss Layer

Convolutional neural networks' final layer, known as theloss layer, is used to punish the discrepancy between the- anticipated output and the true labels. Only one of the K mutually exclusive classes, known as soft max loss, is employed.

6 ResNet Architecture

Deep Residual Learning introduced Residual Neural Networks (ResNet), which are used to build deeper networks that are challenging to train. ResNet has 5 versions and models, including ResNet 18, 34, 50, 101, and152[19]. Reset 18 obtained a Top-5 error rate of 10.92 anda Top-1 error rate of 30.24 percent in these 5 models. It employs skip connections to skip over specific layers andintroduce significant batch normalisation. It has up to 152layers. In comparison to GoogleNet, ResNet has six timesas many layers yet are less sophisticated. Fig.6 illustrates how the ResNet layer is implemented between the convolution layer and the pooling layer, as mentioned in Section 5.

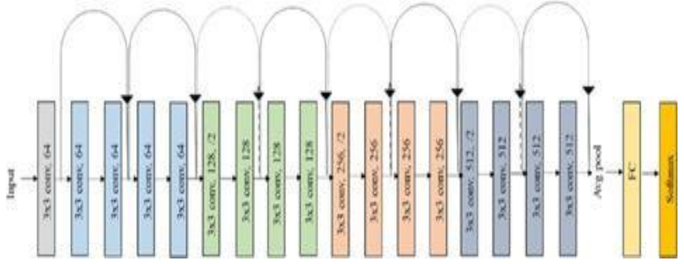

Fig. 5. ResNet-18 Architecture

7 Experimental Results

This project makes use of the Google Collaborator forcomputing resources and the Py-torch deep learning framework for training. Images depicting the creation of burrs are included in the data set. CNN receives the data set, which consists of 450 images. Out of 450 images, 150are used to evaluate the data and 300 are used for training.18 layers in the ResNet-18 experiment's architecture alternate between convolution and pooling layers.

In the CNN design, the Hidden layer contains numerouslayers, including the convolution and pooling layers. Aftermicro milling the substrate a layer is formed at the end of substrate called burr. It can be seen using the microscope and the image in Fig 6 is the microscopic imageof the Burr formation at the end of substrate.

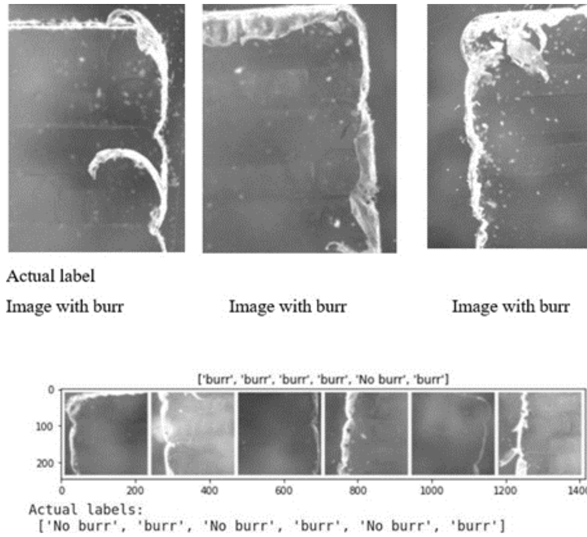

Fig. 6. Microscopic image of Burr images

The output nodes were activated using the SoftMax function, while the hidden nodes were activated using the sigmoid function. Using the softmax activation function atthe output layer, which gives the probability distribution forall data at the output to 1, comes close to classifying imagessince it enables you to identify the output with the highest level of specificity when comparing it to the input data. Thetechnique performs less well when Rectified Linear unit Layer is used in the hidden nodes. Fig. 7 illustrates the relationship between accuracy and training epochs graphically where for each epoch the accuracy value is different and after 10 epochs the accuracy value has been increasing.

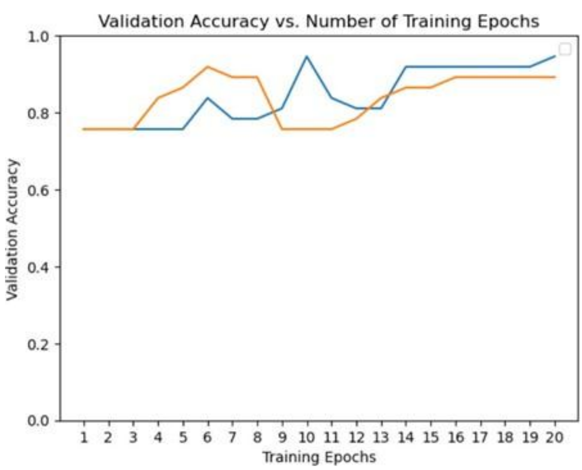

Fig. 7. Graphical Representation of Validation Accuracy vs No of Epochs

The data set is further segmented into test, train and Val datasets after creating a convolutional neural network and training it on the burr image data set. The best accuracy for thetraining dataset is 0.945, while the best accuracy for the Val dataset is 0.945, while the best loss is 0.52. The number of passes (also known as the epoch value) is 20 as shown in Fig.8. At each epoch the accuracy and loss value is varying as shown in the Fig.8, so the highest value of all 20 epochs is considered as the best accuracy value for the data set.

```
Epoch 15/19
----------
train Loss: 0.3011 Acc: 0.8684
val Loss: 0.2125 Acc: 0.9189

Epoch 16/19
----------
train Loss: 0.1737 Acc: 0.9474
val Loss: 0.2211 Acc: 0.9189

Epoch 17/19
----------
train Loss: 0.1982 Acc: 0.9211
val Loss: 0.2297 Acc: 0.9189

Epoch 18/19
----------
train Loss: 0.1564 Acc: 0.9211
val Loss: 0.2018 Acc: 0.9189

Epoch 19/19
----------
train Loss: 0.2427 Acc: 0.8158
val Loss: 0.1721 Acc: 0.9459

Training complete in 2m 42s
Best val Acc: 0.945946
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Fig. 8. Accuracy Value and Lose Value of trained data

8 Conclusion

This paper represents the convolution neural network forthe burr formation images dataset. The experimental results show that the CNN can make good performance with an accuracy rate of 94.5 per cent.

In the future work, the burr formation data set will be trained using SVM, KNN and the results and performance between types of image classification methods will be compared.

References

1. Bal ázs, B. Z., Geier, N., Takács, M., Davim, J. P. (2021). A review on micro-milling: recent advances and future trends. The International Journal of Advanced Manufacturing Technology, 112(3), 655-684
2. Reichenbach, I. G., Bohley, M., Sousa, F. J., Aurich, J. C. (2018). Micromachining of PMMA—manufacturing of burr-free structures with single-edge ultra-small micro end mills. The International Journal of Advanced Manufacturing Technology, 96(9), 3665-3677.
3. Guckenberger, D. J., De Groot, T. E., Wan, A. M., Beebe, D. J., Young, W. (2015). Micromilling: a method for ultra-rapid prototyping of plastic microfluidic devices. Lab on a Chip, 15(11), 2364-2378.
4. Riego, V., S ánchez-González, L., Fernández-Robles, L., Gutiérrez- Fernández, A., Strisciuglio, N. (2021). Burr detection and classifica- tion using RUSTICO and image processing. Journal of computational science, 56, 101485
5. Ko, S. L., Dornfeld, D. A. (1991). A study on burr formation mechanism

6. Wu, M., Chen, L. (2015, November). Image recognition based on deep learning. In 2015 Chinese Automation Congress (CAC) (pp. 542-546). IEEE.
7. Shamsaldin, A. S., Fattah, P., Rashid, T. A., Al-Salihi, N. K. (2019). A study of the convolutional neural networks applications. UKH Journal of Science and Engineering, 3(2), 31-40.
8. Sun, Y., Zhu, L., Wang, G., Zhao, F. (2017). Multi-input convolutional neural network for flower grading. Journal of Electrical and Computer Engineering,2017.
9. LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep learning. nature, 521(7553), 436-444.
10. Hamid, N. A., Sjarif, N. N. A. (2017). Handwritten recognition using SVM, KNN and neural network. arXiv preprint arXiv:1702.00723.
11. Hijazi, S., Kumar, R., Rowen, C. (2015). Using convolutional neural networks for image recognition. Cadence Design Systems Inc.: San Jose, CA, USA, 9, 1.
12. Fujiyoshi, H., Hirakawa, T., Yamashita, T. (2019). Deep learning-based image recognition for autonomous driving. IATSS research, 43(4), 244- 252.
13. Lee, S. H., Dornfeld, D. A. (2007). Prediction of burr formation during face milling using an artificial neural network with optimized cutting conditions. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 221(12), 1705-1714.
14. Hossain, M. A., Sajib, M. S. A. (2019). Classification of image using convolutional neural network (CNN). Global Journal of Computer Science and Technology, 19(D2), 13-18.
15. Haritha, D., Swaroop, N., Mounika, M. (2020, October). Prediction of COVID-19 Cases Using CNN with X-rays. In 2020 5th International Conference on Computing, Communication and Security (ICCCS) (pp. 1-6).
16. Koichi Ito, Hiroya Kawai, Takehisa Okano Takafumi Aoki, “Age and Gender Prediction from Face Images Using Convolutional Neural Net-work”, APSIPAASC 2018, pp. 978-988-14768-5-2
17. Jain, M., Tomar, P. S. (2013). Review of image classification meth- ods and techniques. International journal of engineering research and technology, 2(8), 852-858.
18. Szegedy, C., Toshev, A., Erhan, D. (2013). Deep neural networks for object detection. Advances in neural information processing systems, 26.
19. https://medium.com/@aschandinip/resnet-34-50-101-what-actually-it-is- c63da24ba695.