ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 9| Issue: 7| July 2023|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2023: 8.224 || ISI Value: 1.188

A NOVEL APPROACH TO BANKNOTE CLASSIFICATION USING TRANSFER LEARNING

Rishabh Poojara
Vishwakarma University, Pune

Article DOI: https://doi.org/10.36713/epra13760
DOI No: 10.36713/epra13760

ABSTRACT

Banknote classification is a fundamental component of financial system architecture. Recognition as well as verifying the integrity of banknotes is extremely important for secure transactions at financial institutions. A highly precise multi-classification model can be created using deep learning along with an extensive image dataset of these currency notes featuring them in a myriad of conditions. In addition to providing accuracy, this would also assist reduce the amount of manual intervention required, which would result in greater employee efficiency. This study involves the implementation of transfer learning on a publicly available image dataset of Indian and Thai banknotes. The results of the study will help create an automatic banknote identification and integrity verification layer in the transaction system architecture of financial institutions.

KEYWORDS : *Banknote Classification, Banknote Identification, Multi classification, Machine learning*

INTRODUCTION

In a financial institution, withdrawals and deposits of cash are constantly and simultaneously occurring through ATMs (Automated Teller Machines). The validation layer in the transaction architecture of this machine is used to identify the banknotes as well as verify their integrity through the use of multiple parameters. The validator uses dimension, color and banknote identifiers and symbols to decipher the value of the note before carrying out the transaction. It scans the banknote in multiple spectrums (i.e. visible, magnetic, IR, UV). It employs magnetic sensors to detect the presence of magnetic ink. The validator maintains an electronic template of the banknote which includes any pictures or symbols and their multiple parameters such as size, brightness, contrast etc.

The steps performed by the validator to identify and validate banknote integrity have been carefully considered and incorporated within the architecture of the transaction system of the ATMs since they were pioneered. Despite the fact that significant effort and fine tuning was involved In taking and applying these measures for secure transactions there come circumstances when human intervention becomes necessary. Banknotes are constantly being folded and shoved into wallets and pockets which degrade the quality of the notes, especially in a country like India where the banknotes are entirely made of cotton, which is prone to tearing and staining. Banknotes with stains or tears are not accepted by ATMs since the ATM cannot verify the integrity of the note due to the modified parameters of the note. A slight fold in the corner of a note will often not be accepted by an ATM.

Using deep learning to overcome these problems could increase the competency of the ATMs while reducing the amount of human intervention required. The ATMs would be able to recognize notes with greater precision even in difficult conditions. The banknote can be validated through deep learning in special circumstances where a damaged note is being returned. Computer vision can be used to obtain the code printed on the currency and a pre-trained model trained on a vast database of banknote images can be used to verify the validity of the of the other parameters of the note. The currently active validator of the ATM can be used to match as many parameters as possible on the banknote. All these methods working In synergy could enable the ATM to perform an extremely wide range of tasks. Improving the ATM’s capabilities would enable financial institutions to offer their customers a variety of services on their fingertips which would simultaneously increase the efficiency of the organization as a whole.

Our Study. In this work, we study the usage of transfer learning to facilitate a highly precise validation layer to be incorporated into an ATM’s validator. The ResNet50 architecture has been used with ImageNet weights. As the dataset Is small, using transfer learning was key to obtain a high accuracy while maintaining an efficient model as the model already holds some knowledge due to the pre-training. The dataset also requires custom tuning of the model with a lower learning rate as it is essential to carefully traverse through the dataset and to obtain high precision. Using a pre-trained model with custom refinements in accordance with the dataset was beneficial as it it helped the model converge in less epochs compared to a manually trained convolutional neural network.

The goal of this paper is to provide insight on the involvement of deep learning in the validation architecture of ATMs.

RELATED WORK

ResNets can be used to overcome the vanishing gradient problem during the training of very deep convolutional networks [1]. Wide residual networks, which use wider convolutional layers to improve performance. Wider networks can achieve comparable or even better accuracy than deeper networks while requiring fewer parameters. [3]

K. Patil et al. [2] proposed the capturing of images in different lighting conditions as well as physical conditions of the objects. This would create an optimal dataset for both training and validation of models.

Transferring of features from pre-trained models as well as fine tuning the neural networks can lead to high accuracy even with limited target domain data [4]. Parallels have been drawn between human and computer learning regarding knowledge transfer from previous situations to facilitate learning in related tasks [5].

METHODOLOGY

Data set

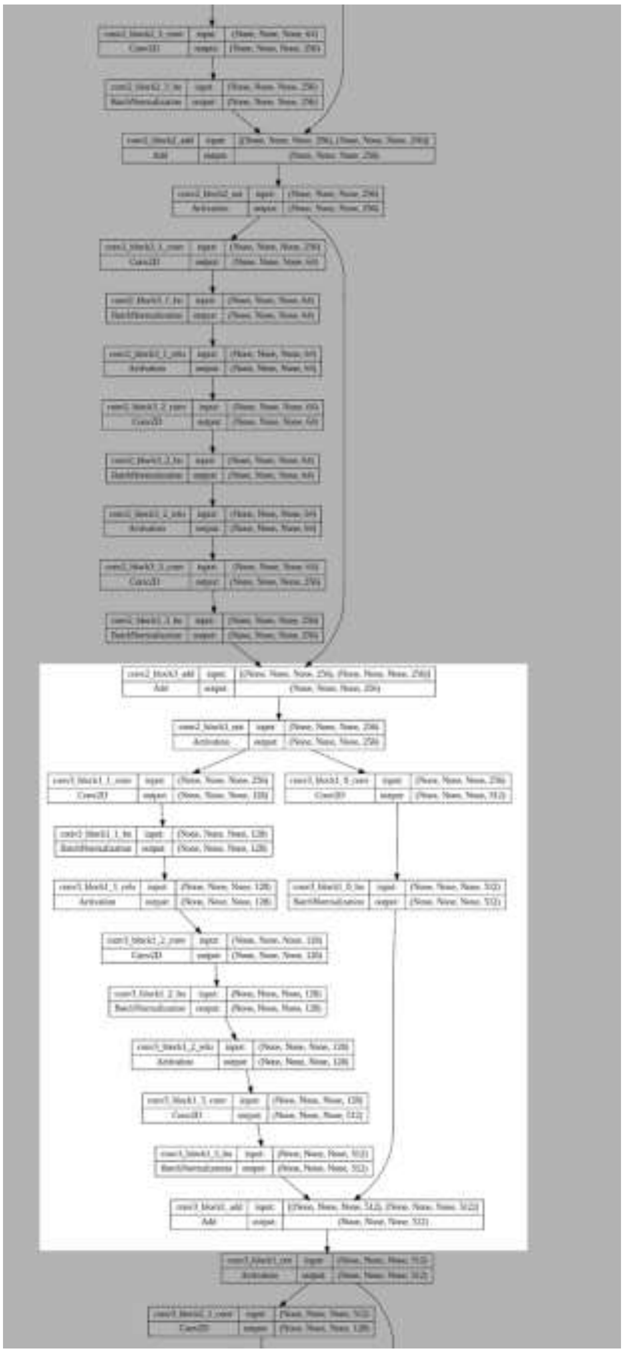
The following factors make the development of a banknote dataset extremely important: First, accurate banknote recognition is a task that automated teller machines and currency recognition machines must complete; second, it is necessary to develop a system that can determine whether a banknote is genuine; and third, visually impaired individuals frequently struggle with banknote recognition.

The dataset consists of Indian and Thai banknotes. The Indian banknotes are classified into ten classes. The Thai banknotes are classified into five classes. Though pictures have been taken in a variety of light conditions and physical conditions, the pictures feature shadows, bright lights and cluttered environment. Additionally, pictures of partially folded and stained banknotes are used. These conditions are instrumental for the training of an accurate model.

Model

Transfer learning leverages pre-trained models to provide high accuracy and efficiency models. ResNet50 when used as a pre-trained model provides a high accuracy without manual adjustments. One of the key innovations of ResNet50 is the use of residual blocks. These blocks address the challenge of training very deep neural networks by mitigating the vanishing gradient problem, which can hinder the learning process. The residual blocks introduce skip connections, that enable the direct flow of information across layers.The skip connections in ResNet50 allow the network to learn residual mappings, capturing the difference or residual between the desired output and the current representation. By propagating the residual information, the network can effectively tackle the degradation problem that arises with deeper networks, where adding more layers leads to reduced accuracy.

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 9| Issue: 7| July 2023|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2023: 8.224 || ISI Value: 1.188

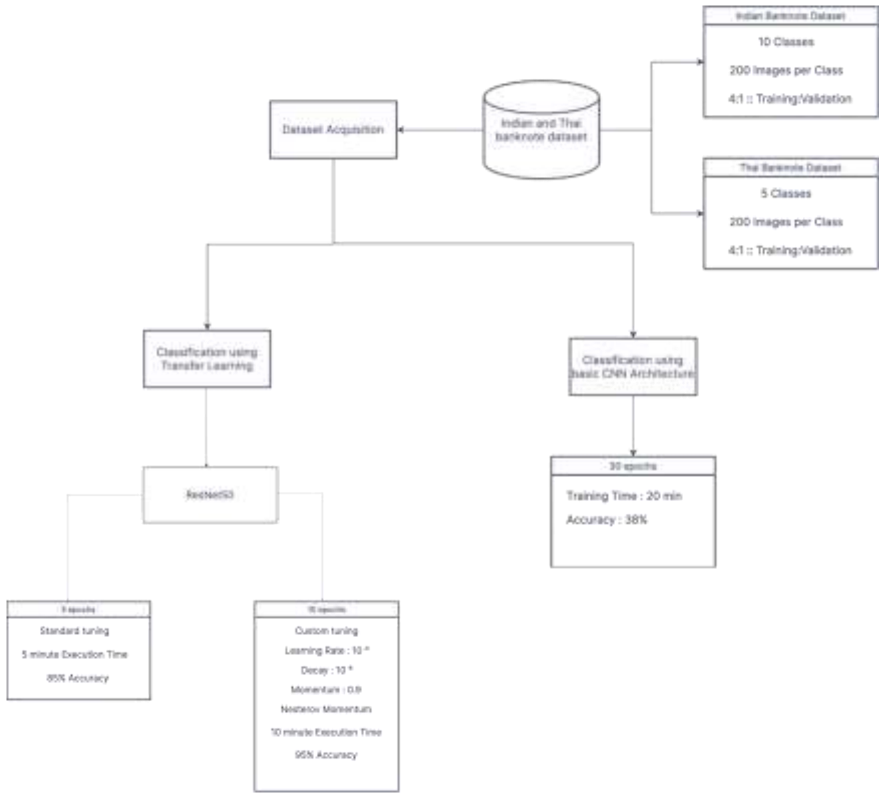


Section of the ResNet50 model with the skip connection

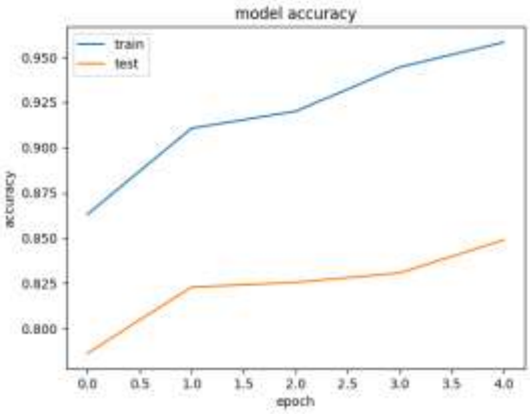
On training the model with no custom tuning an accuracy of about 85% was obtained. An accuracy significantly higher is required to make the model fit for financial institutions. Stochastic gradient descent is used to optimize the path to the global minima .Extreme fine tuning of the model is required to get a desired output. Decreasing the learning ratite the order of $10^{-3,}$ setting the decay to the order of 10^{-6}, and setting the momentum to 0.9 helped traverse the dataset with precision. Nesterov momentum is used to smooth out oscillations and for acceleration near convergence.

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 9| Issue: 7| July 2023|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2023: 8.224 || ISI Value: 1.188

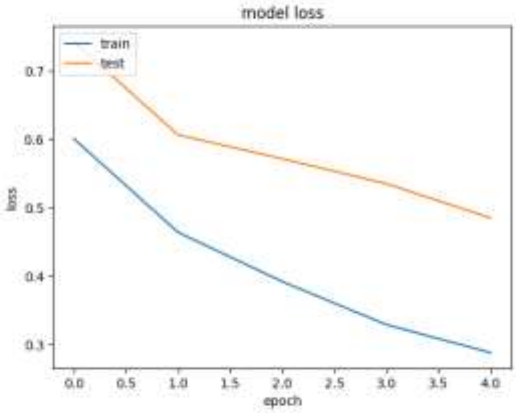
```
/usr/local/lib/python3.10/dist-packages/keras/optimizers/legacy/gradient_descent.py:114: UserWarning: The `lr` argument is deprecated, use `learning_rate` instead.
  super().__init__(name, **kwargs)
Epoch 1/10
25/25 [==============================] - 69s 3s/step - loss: 0.7501 - accuracy: 0.8769 - val_loss: 0.4324 - val_accuracy: 0.8672
Epoch 2/10
25/25 [==============================] - 56s 2s/step - loss: 0.3835 - accuracy: 0.9806 - val_loss: 0.2955 - val_accuracy: 0.8958
Epoch 3/10
25/25 [==============================] - 55s 2s/step - loss: 0.2142 - accuracy: 0.9831 - val_loss: 0.2474 - val_accuracy: 0.9089
Epoch 4/10
25/25 [==============================] - 55s 2s/step - loss: 0.1385 - accuracy: 0.9806 - val_loss: 0.2116 - val_accuracy: 0.9271
Epoch 5/10
25/25 [==============================] - 55s 2s/step - loss: 0.1000 - accuracy: 0.9969 - val_loss: 0.2249 - val_accuracy: 0.9167
Epoch 6/10
25/25 [==============================] - 55s 2s/step - loss: 0.0771 - accuracy: 0.9963 - val_loss: 0.1890 - val_accuracy: 0.9375
25/25 [==============================] - 54s 2s/step - loss: 0.0616 - accuracy: 0.9981 - val_loss: 0.1861 - val_accuracy: 0.9349
Epoch 8/10
25/25 [==============================] - 56s 2s/step - loss: 0.0480 - accuracy: 0.9981 - val_loss: 0.1739 - val_accuracy: 0.9427
Epoch 9/10
25/25 [==============================] - 55s 2s/step - loss: 0.0416 - accuracy: 0.9994 - val_loss: 0.1616 - val_accuracy: 0.9479
Epoch 10/10
25/25 [==============================] - 52s 2s/step - loss: 0.0359 - accuracy: 0.9969 - val_loss: 0.1644 - val_accuracy: 0.9505
<keras.callbacks.History at 0x7f8440177970>
```



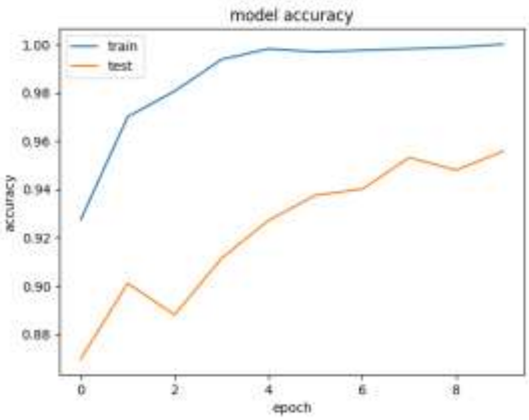
ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 9| Issue: 7| July 2023|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2023: 8.224 || ISI Value: 1.188



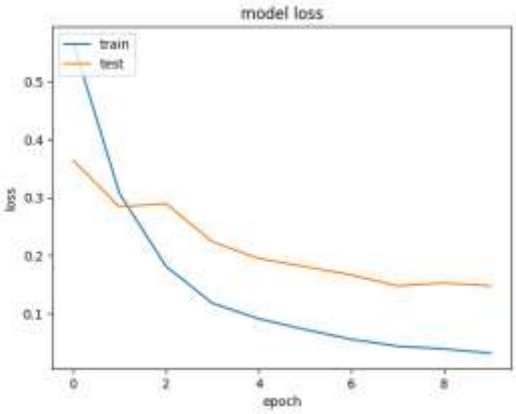
Visualization of accuracy obtained on using ResNet50 without custom tuning



Visualization of loss using ResNet50 without custom tuning

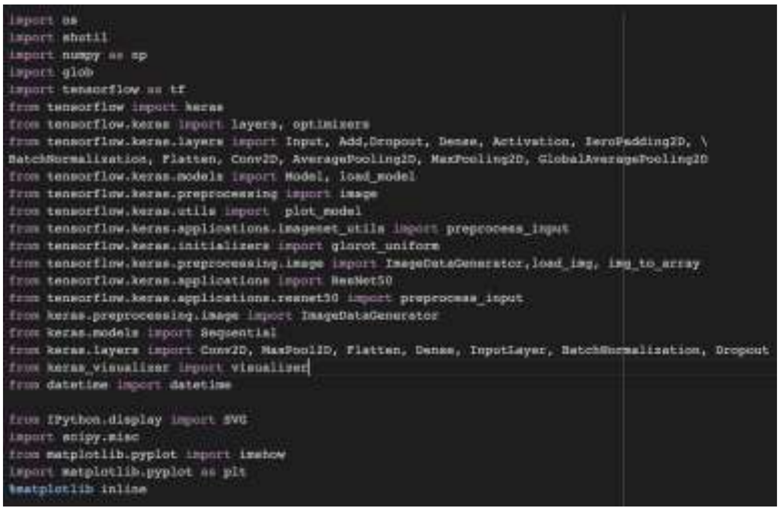


Visualization of accuracy obtained on using ResNet50 with custom tuning



Visualization of loss using ResNet50 with custom tuning

Libraries Used



```
import os
import shutil
import numpy as np
import glob
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers, optimizers
from tensorflow.keras.layers import Input, Add,Dropout, Dense, Activation, ZeroPadding2D, \
BatchNormalization, Flatten, Conv2D, AveragePooling2D, MaxPooling2D, GlobalAveragePooling2D
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.preprocessing import image
from tensorflow.keras.utils import  plot_model
from tensorflow.keras.applications.imagenet_utils import preprocess_input
from tensorflow.keras.initializers import glorot_uniform
from tensorflow.keras.preprocessing.image import ImageDataGenerator,load_img, img_to_array
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.applications.resnet50 import preprocess_input
from keras.preprocessing.image import ImageDataGenerator
from keras.models import Sequential
from keras.layers import Conv2D, MaxPool2D, Flatten, Dense, InputLayer, BatchNormalization, Dropout
from keras_visualizer import visualizer
from datetime import datetime

from IPython.display import SVG
import scipy.misc
from matplotlib.pyplot import imshow
import matplotlib.pyplot as plt
%matplotlib inline
```

Why ResNet was chosen

Compared to other available pre-trained models, ResNet has a deeper architecture enabling it to learn intricate details and patterns within the images. Even though the network is deep, the usage of residual blocks and skip connections enable the model to overcome the vanishing gradient problem. It allows the gradients to flow directly from earlier layers to later layers without any transformation. This helps the model adapt better to complex datasets.

The skip connections also provide shorter paths for the flow of information between layers. This leads to a reduction in the number of parameters. ResNet is more efficient in terms of memory usage and computational resources while providing an extremely high accuracy compared to other pre-trained models.

CONCLUSION

Image classification using the ResNet architecture has proven to be a powerful and effective approach for various computer vision tasks. The deep residual networks have addressed the challenge of training deep neural networks by introducing skip connections that enable the network to learn residual mappings effectively. This architectural design has allowed ResNet to achieve remarkable precision and also outperforms other models significantly on benchmark datasets. ResNet has exhibited strong generalization capabilities, making it robust to noise, occlusions, and variations in lighting conditions.

Employing ResNet with small datasets has demonstrated its potential to address the challenges of limited data availability in image classification tasks. The ResNet architecture, with its deep residual networks, has showcased the ability to learn complex representations even with a reduced number of training samples. Fine-tuning the model to adapt to a smaller dataset worked exceptionally well with the ResNet architecture, resulting in high accuracy.

REFERENCES

1. *He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). https://doi.org/10.1109/cvpr.2016.90*
2. *Suryawanshi, Y., Patil, K., & Chumchu, P. (2022). VegNet: Dataset of vegetable quality images for machine learning applications. Data in Brief, 45, 108657*
3. *Zagoruyko, S., & Komodakis, N. (2016). Wide residual networks. Procedings of the British Machine Vision Conference 2016. https://doi.org/10.5244/c.30.87*
4. *Yosinski, J., Clune, J., Bengio, Y., & Lipson, H. (2014). How Transferable Are Features in Deep Neural Networks? Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2, 3320–3328. Presented at the Montreal, Canada. Cambridge, MA, USA: MIT Press.*
5. *Flennerhag, S., Moreno, P. G., Lawrence, N., & Damianou, A. (2019). Transferring knowledge across learning processes. ICLR 2019. Retrieved from https://www.amazon.science/publications/transferring-knowledge-across-learning-processes*
6. *Chumchu, P., & Patil, K. (2023). Dataset of cannabis seeds for machine learning applications. Data in Brief, 47, 108954.*
7. *Laad, M., Kotecha, K., Patil, K., & Pise, R. (2022). Cardiac Diagnosis with Machine Learning: A Paradigm Shift in Cardiac Care. Applied Artificial Intelligence, 36(1), 2031816.*
8. *Pise, R., Patil, K., Laad, M., & Pise, N. (2022). Dataset of vector mosquito images. Data in Brief, 45, 108573.*
9. *Meshram, V., & Patil, K. (2022). Border-Square net: a robust multi-grade fruit classification in IoT smart agriculture using feature extraction based Deep Maxout network. Multimedia Tools and Applications, 81(28), 40709-40735.*
10. *Meshram, V., Patil, K., Meshram, V., Dhumane, A., Thepade, S., & Hanchate, D. (2022, August). Smart Low Cost Fruit Picker for Indian Farmers. In 2022 6th International Conference On Computing, Communication, Control And Automation (ICCUBEA) (pp. 1-7). IEEE.*
11. *Pise, R., Patil, K., & Pise, N. (2022). Automatic Classification Of Mosquito Genera Using Transfer Learning. Journal of Theoretical and Applied Information Technology, 100(6), 1929-1940.*
12. *Bhutad, S., & Patil, K. (2022). Dataset of road surface images with seasons for machine learning applications. Data in brief, 42, 108023.*
13. *Bhutad, S., & Patil, K. (2022). Dataset of Stagnant Water and Wet Surface Label Images for Detection. Data in Brief, 40, 107752*
14. *Sonawani, S., Patil, K., & Natarajan, P. (2023). Biomedical signal processing for health monitoring applications: a review. International Journal of Applied Systemic Studies, 10(1), 44-69.*
15. *Meshram, V., Patil, K., & Chumchu, P. (2022). Dataset of Indian and Thai banknotes with annotations. Data in brief, 41, 108007.*
16. *Meshram, V., & Patil, K. (2022). FruitNet: Indian fruits image dataset with quality for machine learning applications. Data in Brief, 40, 107686.*
17. *Meshram, V., Patil, K., Meshram, V., Hanchate, D., & Ramkteke, S. D. (2021). Machine learning in agriculture domain: A state-of-art survey. Artificial Intelligence in the Life Sciences, 1, 100010.*
18. *Meshram, V. A., Patil, K., & Ramteke, S. D. (2021). MNet: A Framework to Reduce Fruit Image Misclassification. Ingénierie des Systèmes d Inf., 26(2), 159-170.*
19. *Sonawani, S., Patil, K., & Chumchu, P. (2021). NO2 pollutant concentration forecasting for air quality monitoring by using an optimised deep learning bidirectional GRU model. International Journal of Computational Science and Engineering, 24(1), 64-73.*
20. *Testani, M. V., & Patil, K. (2021). Integrating Lean Six Sigma and Design Thinking for a Superior Customer Experience.*
21. *Meshram, V., Patil, K., & Hanchate, D. (2020). Applications of machine learning in agriculture domain: A state-of-art survey. Int. J. Adv. Sci. Technol, 29, 5319-5343.*
22. *Meshram, V. V., Patil, K., Meshram, V. A., & Shu, F. C. (2019). An astute assistive device for mobility and object recognition for visually impaired people. IEEE Transactions on Human-Machine Systems, 49(5), 449-460.*
23. *Patil, K., Laad, M., Kamble, A., & Laad, S. (2019). A consumer-based smart home with indoor air quality*

monitoring system. IETE Journal of Research, 65(6), 758-770.

24. *Patil, K., Jawadwala, Q., & Shu, F. C. (2018). Design and construction of electronic aid for visually impaired people. IEEE Transactions on Human-Machine Systems, 48(2), 172-182.*
25. *Patil, K., Laad, M., Kamble, A., & Laad, S. (2018). A consumer-based smart home and health monitoring system. International Journal of Computer Applications in Technology, 58(1), 45-54.*
26. *Shah, R., & Patil, K. (2018). A measurement study of the subresource integrity mechanism on real-world applications. International Journal of Security and Networks, 13(2), 129-138.*
27. *Shah, R. N., & Patil, K. R. (2017). Securing third-party web resources using subresource integrity automation. International Journal on Emerging Trends in Technology, 4(2), 5.*
28. *Patil, K. (2017). An insecure wild web: A large-scale study of effectiveness of web security mechanisms. Vishwakarma Institute of Information Technology, Pune.*
29. *Kawate, S., & Patil, K. (2017). Analysis of foul language usage in social media text conversation. International Journal of Social Media and Interactive Learning Environments, 5(3), 227-251.*
30. *Kawate, S., & Patil, K. (2017). An Approach For Reviewing And Ranking The Customers'reviews Through Quality Of Review (QoR). ICTACT Journal on Soft Computing, 7(2).*
31. *Patil, K. (2017). Isolating malicious content scripts of browser extensions. International Journal of Information Privacy, Security and Integrity, 3(1), 18-37.*
32. *Jawadwala, Q., & Patil, K. (2016, December). Design of a novel lightweight key establishment mechanism for smart home systems. In 2016 11th International Conference on Industrial and Information Systems (ICIIS) (pp. 469-473). IEEE.*
33. *Patil, K. (2016). Preventing click event hijacking by user intention inference. ICTACT Journal on Communication Technology, 7(4), 1408-1416*
34. *Shah, R., & Patil, K. (2016). Evaluating effectiveness of mobile browser security warnings. ICTACT Journal on Communication Technology, 7(3), 1373-1378.*
35. *Patil, K., & Frederik, B. (2016). A Measurement Study of the Content Security Policy on Real-World Applications. Int. J. Netw. Secur., 18(2), 383-392.*
36. *Patil, D. K., & Patil, K. (2016). Automated Client-side Sanitizer for Code Injection Attacks. International Journal of Information Technology and Computer Science, 8(4), 86-95.*
37. *Patil, K. (2016). Request dependency integrity: validating web requests using dependencies in the browser environment. International Journal of Information Privacy, Security and Integrity, 2(4), 281-306.*
38. *Meshram, V., Meshram, V., & Patil, K. (2016). A survey on ubiquitous computing. ICTACT Journal on Soft Computing, 6(2), 1130-1135.*
39. *Patil, D. K., & Patil, K. (2015). Client-side automated sanitizer for cross-site scripting vulnerabilities. International Journal of Computer Applications, 121(20), 1-7.*
40. *Omanwar, S. S., Patil, K., & Pathak, N. P. (2015). Flexible and fine-grained optimal network bandwidth utilization using client side policy. International Journal of Scientific and Engineering Research, 6(7), 692-698.*
41. *Kurle, A. S., & Patil, K. R. (2015). Survey on privacy preserving mobile health monitoring system using cloud computing. International Journal of Electrical, Electronics and Computer Science Engineering, 3(4), 31-36.*
42. *Dong, X., Patil, K., Mao, J., & Liang, Z. (2013, July). A comprehensive client-side behavior model for diagnosing attacks in ajax applications. In 2013 18th International Conference on Engineering of Complex Computer Systems (pp. 177-187). IEEE.*
43. *Patil, K., Vyas, T., Braun, F., Goodwin, M., & Liang, Z. (2013, July). Poster: UserCSP-user specified content security policies. In Proceedings of Symposium on Usable Privacy and Security (pp. 1-2).*
44. *Patil, K., Dong, X., Li, X., Liang, Z., & Jiang, X. (2011, June). Towards fine-grained access control in javascript contexts. In 2011 31st International Conference on Distributed Computing Systems (pp. 720-729). IEEE.*
45. *Suryawanshi, Y. C. (2021). Hydroponic cultivation approaches to enhance the contents of the secondary metabolites in plants. In Biotechnological Approaches to Enhance Plant Secondary Metabolites (pp. 71-88). CRC Press.*
46. *Kanorewala, B. Z., & Suryawanshi, Y. C. (2022). The Role of Alternate Nostril Breathing (Anuloma Viloma) Technique in Regulation of Blood Pressure. Asian Pacific Journal of Health Sciences, 9(2), 48-52.*
47. *Suryawanshi, Y., & Patil, K. (2023). Advancing Agriculture Through Image-Based Datasets In Plant Science: A Review. EPRA International Journal of Multidisciplinary Research (IJMR), 9(4), 233-236.*