VFAST Transactions on Software Engineering
https://vfast.org/journals/index.php/VTSE@ 2024, ISSN(e): 2309-3978, ISSN(p): 2411-6246
Volume 12, Number 4, October-December 2024 pp:87-98

Automated Detection and Recognition of Seven-Segment Digits from Electric Meters Utilizing Digital Image Processing and Machine Learning

Hamza Haseeb [1], **Malik Tahir Hassan** [1], **Afnan Iftikhar** [1*], **Ayesha Asmat** [1]

[1]School of Systems and Technology, University of Management and Technology, Lahore, Pakistan

Keywords: *Digit recognition, digit detection, electric meters, Seven-Segment Digits*

Journal Info:
Submitted:
October 04, 2024
Accepted:
November 25, 2024
Published:
December 01, 2024

Abstract

With the rise of computers and their importance in various fields, traditional electric meters in Pakistan have been replaced by digital electric meters. These digital meters are more accurate and easier to read as they display readings using Seven-Segment Digits. Currently, for billing purposes, human meter readers manually capture images of these meters using cameras or smartphones, and the readings are then recorded manually. This process is time-consuming and prone to errors due to human involvement.Automating the reading of meter images can significantly improve the accuracy and efficiency of the billing process. However, this task is challenging because the captured images can vary in quality, scale, orientation, lighting conditions, and other factors.To address these challenges, we experimented with different machine learning and deep learning models to automatically recognize meter readings from captured images. Five models were trained and evaluated: K-Nearest Neighbors (KNN), Decision Tree, Support Vector Machine (SVM), Random Forest, and Convolutional Neural Network (CNN). These models were tested on real meter data for digit recognition, achieving an accuracy of up to 98%. This promising result demonstrates the potential for fully automating the meter reading process in the future.

***Correspondence author email address:** afnaniftikhar@umt.edu.pk
DOI: 10.21015/vtse.v12i4.1923

1 Introduction

Currently, images of the displays of these meters are taken manually by a human meter reader by using different devices such as cameras, mobile phones, etc. Electricity providers send bills to the consumer after reading these images, which is a long and time-consuming process. The images are taken at various times of the day, resulting in differences in light intensity. Due to manual image capturing, these are prone to errors such as blurriness, tilting, shadows, and poor contrast, thus leading to the issues in reading. Therefore, there is a need to automate the task of reading data from images to increase the speed as well as to avoid inaccuracies.

In digital electric meters, the decimal numbers are represented using a seven-segment display. In seven-segment display, seven LED bars are arranged in such a way that shape of figure eight is formed as shown in ***Figure 1***. This individual segment can display the numbers 0-9. In case of electric meters only number 0-9 are displayed by lightning the relevant segment [1]. In this research, we aim to accurately detect and recognize seven-segment digits from captured images of digital electric meters. For this purpose, different machine learning and deep learning approaches are used. Detecting and recognizing seven-segment digits from collected data samples can be helpful to improve the procedure of billing systems.

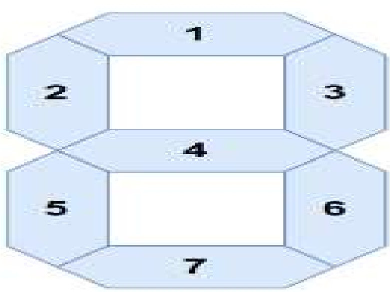

Figure 1. Seven-Segment Display

2 Background and related work

Research on seven-segment numeral recognition in meters is sparse, with some studies focusing on this topic and some on the application in energy meters. In the literature, both image-processing and machine learning-based approaches have been applied with different degrees of accuracy. For instance, [2] used a support vector machine (SVM) classifier to perform digit recognition. The author used mobile camera-captured images, firstly color edge detection was applied to detect and find the region of interest (ROI) and localize the meter display area. To enhance the digits preprocessing using Morphological Black-hat operation and Adaptive thresholding were performed. In this work, the SVM classifier was trained on the dataset of 500 digits whereas for testing 175 images were used achieving an accuracy of 97%.

In research [3], the author presented a dataset "YUVA EB Dataset [4]" of 169 energy meters that contain 985 seven-segment numerals captured from a digital camera. These images are captured in daylight as well as in night, also this dataset contains blurred and tilted images for better testing of any approach. For the detection of seven segment numerals, the OCR function available with MATLAB was trained and an accuracy of 93.17 was achieved. To reduce the manual effort and to deal with the issue of limited datasets authors [5] generated an algorithm to create synthetic training images automatically, and then machine learning approach ResNetV2 was applied and achieved an accuracy of 96.8%. The model was trained on 225,337 images for digit estimation.

In another study [6], a resource-efficient approach is presented. The authors used the Lightweight neural network to detect digits on meters. Digits are recognized and the data were stored on an Android application in real-time. 96% accuracy is achieved with the dataset of 41,607 images. In a recent paper [7] authors presented a comparative analysis of text recognizing models for the detection of 7 segment numerals. As per the experiments, DBNet from Paddle OCR performed best for detecting text whereas PARSeq has the best accuracy of 56.97% for seven segment numerals. The models are tested on 7 Seg dataset [8].

In several approaches [8–13] data were collected from medical devices such as blood pressure monitors, gluco-meters, etc., and automatically analyzed using image processing. In [9] a dataset of 138240 images were trained and tested using a Neural Network with an accuracy of 93%. In [10] deep learning model faster-RCNN was applied on 400 images and 94% accuracy was achieved. The recognition of seven segment numerals has several use cases in medicine, In [14] a real-time embedded monitoring system was developed to monitor Intensive care unit patients.

In [17] an image-based framework for reading electrical energy meters, focusing on extracting the digit regions from meter images and recognizing them to record consumed units. By integrating these readings

Table 1. Summary of the literature about seven-segment digit recognition approaches

Reference no	Paper title	Algorithm	Accuracy	Dataset
[2]	Recognition of Seven-Segment Displays from Images of Digital Energy Meters	Support Vector Machine	97%	175 images
[3]	Text detection and recognition in raw image dataset of seven segment digital energy meter display	OCR	93.17%	169 images
[5]	Automatic Generation Of Seven-Segment Display Image for Machine-learning-Based Digital Meter Reading	ResNetV2	96.5%	225,557 synthetic images
[6]	Lightweight CNN based meter digit recognition	Lightweight CNN	95%	41,607 images
[7]	Detecting and recognizing seven segment digits using a deep learning approach	PaddleOCR	85.97%	189 images
[8]	Automated method for detecting and reading seven-segment digits from images of blood glucose meters and blood pressure monitors	CNN	93%	138,240 images
[10]	An Integrated Technique for Detecting Seven-Segment Digits on Medical Devices	Faster RCNN	94%	400 images
[12]	Utilizing Smartphone-Based Machine Learning in Medical Monitor Data Collection: Seven Segment Digit Recognition	Random Forest	98.2%	110 images
[14]	ROMI: A Real-Time Optical Digit Recognition Embedded System for Monitoring Patients in Intensive Care Units	CNN	97%	14 million images
[15]	Deep learning-based autonomous real-time digital meter reading recognition method for natural scenes	YOLO	99.6%	SVSU-DM dataset
[16]	Image-based automatic energy meter reading using deep learning	YOLO	95%	10,000 images

with serial numbers and energy meter data, we enable a real-time, automated billing system powered by the Internet of Things (IoT) and a graphical user interface. The process faces challenges such as partial occlusions from dust, variations in orientation and scale due to camera positioning, and uneven illumination caused by shadows.

To address these issues, Researchers compare the state-of-the-art deep learning algorithm YOLO (You Only Look Once) with traditional handcrafted features for text extraction and recognition. Using a dataset of 10,000 annotated images, expanded through data augmentation techniques like rotation and scaling, they train and evaluate these methods. YOLO demonstrates superior performance, achieving a 98% recognition accuracy and proving robust against image variations compared to traditional approaches.

Enriquez, E.A., et al. [17] in their research compare traditional machine learning models for feature extraction with convolution neural network models. Machine learning models which are used are K-Nearest Neighbor (KNN), support vector machine (SVM), and Mahalanobis distance. At the foundation level steps taken out contains preprocessing, segmentation, and feature extraction. Preprocessing involves noise reduction and image binarization. Feature extraction using regular traditional machine learning methods involves some parameters like Hu Invariants Moments, Zoning, Horizontal cell projection, Local line fitting, and projection histograms. Researchers concluded that the result which was carried out by convolution neural network was much better than machine learning methods.

The paper [15] presents a deep learning-based approach to recognize digital meter readings in natural scenes. The author applied YOLO-CPDM and YOLO-EERRM to find region of interest and to extract digits from the meter respectively. The approach was tested on the SYSU-DM dataset and two public datasets and achieved an accuracy up to 99.6%. In this article [16], the author also applied YOLO and achieved 98% recognition rate with the dataset of 10,000 images.

3 Material and Method

Steps required for data acquisition and its preparation according to the required models are described as follow.

3.1 Data Acquisition

For this research, a data set consisting of a total of 494 images of electric meters has been used. These images were collected from the Pakistan Water and Power Development Authority (WAPDA). ***Figure 2*** displays a sample image captured from the digital electric meter by the meter reader. The area captured in the pictures varies; some pictures capture more area, while others capture less. Different area segments show different information such as unit reading, indicator light showing information about earth, power, neutral, etc. In addition to the different areas captured, the pictures were also taken from different angles or sides. Moreover, there are other issues such as blurriness, tilting, shadows, poor contrast, low visibility, or distortion/noise. These images were then preprocessed using different approaches which are discussed in the next section.

Figure 2. Electric Meter Image

3.2 Preprocessing for Digit Recognition

Preprocessing raw images prior to model training can enhance classifier accuracy. Raw images typically contain noise that complicates digit recognition. The following sections discuss a sequence of image processing techniques applied to address this challenge.

3.3 Extraction of Region of interest

To identify the region of interest (ROI), i.e., LCD screen showing the unit reading/digits OpenCV library tools have been used for this purpose. LCD screen showing the unit reading/digit is highlighted in ***Figure 3***. For this purpose, different steps have been applied such as image resizing, grayscale conversion, a Gaussian blur, canny edge detection, and threshold. As the images captured are of different sizes, first they were resized to 500 x 500 pixels.

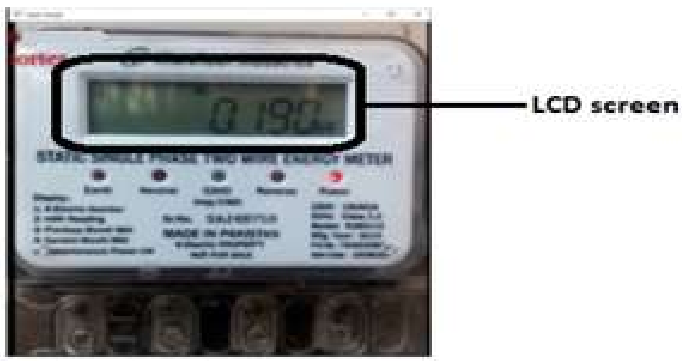

Figure 3. Highlighted ROI

3.4 Grayscale Conversion

The captured images were in RGB format. After resizing, the input image was then converted into a grayscale im-age. Conversion of RGB images to grayscale images helps in reducing noise, decreasing color complexity, simplifying, and increasing the processing speed of the algorithm, thus resulting in reduced computational requirements. Grayscale conversion can help in image segmentation and object detection. ***Figure 4*** shows the image after applying grayscale conversion

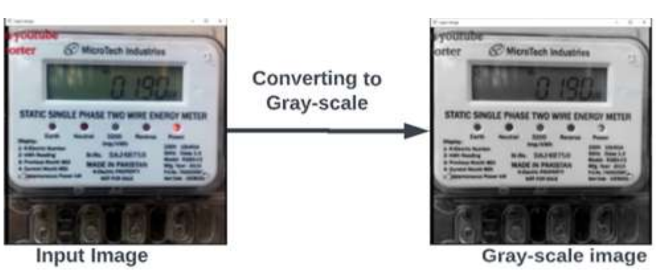

Figure 4. Grayscale Conversion

3.5 Gaussian Blur Filter

While processing images Gaussian blur filter is applied as a preprocessing step to reduce the image noise while keeping image information secure. After removing the noise, the pixel size of the image is also reduced. For this purpose, Gaussian Blur filter of 5x5 kernel was applied to the greyscale image. ***Figure 5*** shows the image after applying the Gaussian blur filter.

Figure 5. Gaussian Blurred Image

3.6 Canny Edge Detection

Edges detection in digital images is the process of identifying the edges: outlines or boundaries in images, which may occur due to sudden transformations in the intensity of light, texture, and color. As edges in the image characterize the boundaries of any object thus after edge detection, we can easily extract our ROI which results in simplifying image analysis as the data to be processed is reduced [18]. For this purpose, canny edge detection has been used. ***Figure 6***, shows the image after applying canny edge detection, where the outline/ edges of LCD screen are clearly visible.

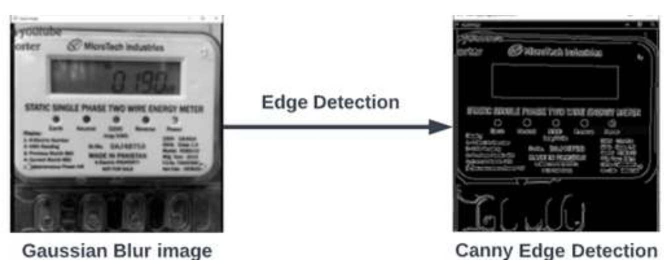

Figure 6. Canny Edge Detection

3.7 Finding Contours

Contours detection using OpenCV libraries was then applied to identify the LCD. Contours represent the continuous closed curves that outline the boundaries of different meaningful regions or objects in any image [19]. The assumption is that if the contours have four vertices, it will potentially be the required region. The extracted contours are then sorted by their areas. Applying contours approximation by looping over the given list individually, the contours with the largest area mark our region of interest i.e., LCD. ***Figure 7*** represents the extracted region of interest, after identifying the contours.

Figure 7. Extraction of ROI

3.8 Threshold

Binary thresholding was then applied as a last preprocessing step. The thresholding is a technique used to convert a grayscale image into a binary image, where every pixel is assigned a value of either 0 or 255. The binary image is used then to segment objects from the background. In our case, it helps in segmenting our digits from the background. ***Figure 8*** represents the binary image after applying the threshold.

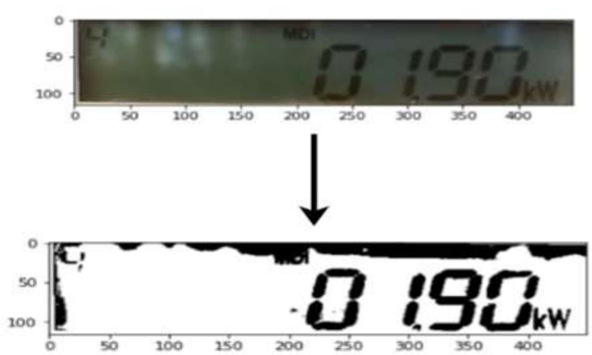

Figure 8. Threshold Application

3.9 Digit Segmentation

After preprocessing of images, image segmentation was done to segment the digits. Segmentation of an image is also known as partitioning of a digital image into several smaller segments. The objective of segmentation is to simplify digital images so we can use these segments to perform multiple operations like the digit's recognition. It also makes it easy to analyze and makes the digital image more meaningful. For this purpose, two techniques can be used, image processing approach and Artificial Intelligence (AI) approach. The AI approach contains multiple CNN, RNN and ML models whereas in image processing approach pixels are used to find the contours of each individual digit to separate them. We use an image processing approach to find strongly connected components in any image. ***Figure 9*** represents the segmented digits from images. After applying digit segmentation these digits can be given to the models for training or testing. After segmentation from each image of our data set approximately 5 segmented digits were generated. Thus resulting into 2470 images of digits. For training, of course, these digits need to be assigned labels first.

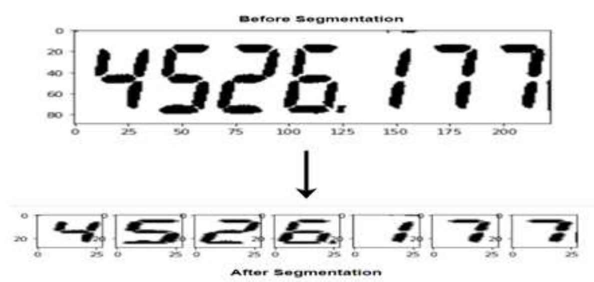

Figure 9. Digit Segmentation

3.10 Assigning Class Label to Data

After segmenting the digits, class labels are then assigned to images. As our data is in the form of images the label assigned to each image file is the number (digit) contained in it. Sample data of image along with its label is shown in ***Figure 10***.

3.11 Data Augmentation

Data augmentation is a technique that is used to enhance the quality and size of the dataset for training to have better accuracy. After segmenting the digits, we performed data augmentation techniques such as zooming, rotation, adjusting random brightness, and introducing distortion. Each digit image was passed to the augmenter to obtain 10 samples for each image,

Figure 10. Image with Class Label

thus resulting in 24,700 images in all. After augmenting the data, file names of the images were appended with numbers from 1 to 10 as shown in ***Figure 11***.

Figure 11. Class Labels After Augmentation

3.12 Supervised Model Construction

For digit recognition, the data set of digital electric meters have been used to train following machine learning and deep learning classifiers.

1. Machine learning classifiers include K-Nearest Neighbor (KNN) [20], Decision Tree [21], Support Vector Machine (SVM) [22], and Random Forest [23].
2. Deep learning model used is the Convolution Neural Network (CNN) [17]. ***Figure 12*** shows the process flow for our work.

3.13 Classification Dataset and Implementation

The dataset of total 24,700 digits images was split into 70% - 30% ratio i.e., 17,290 images for training and 7,417 images for testing respectively. Using these images, 5 different classifiers were validated. The "scikit-learn" library in python has been used for experimental evaluation.

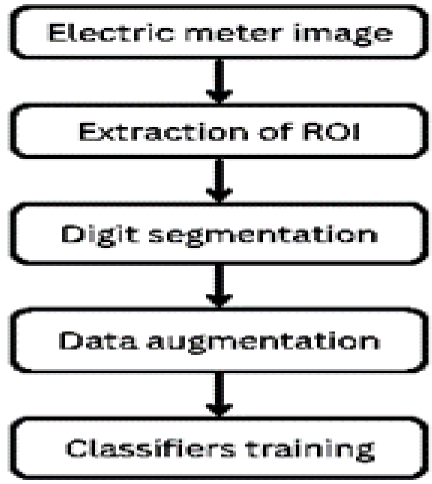

Figure 12. Process Flow Diagram of the Proposed Method

4 Results And Discussion

For the performance evaluation of our trained models measures such as precision, recall, F-measure and accuracy were used. The results of various experiments are briefly discussed in the following sections.

4.1 Results for K-Nearest Neighbor classifier

During the testing phase, KNN predicted 7,417 images and achieved an accuracy of 95.22%. ***Table 2*** is showing the confusion matrix. There are ten rows and ten columns as the class labels are 0 to 9, the digits.

Table 2. KNN Confusion Matrix

727	6	0	0	0	2	4	2	2	2
7	677	0	3	2	2	1	17	1	9
3	2	683	9	0	1	6	1	0	3
5	2	2	708	1	2	5	8	1	15
8	4	0	2	714	3	1	0	2	15
2	0	1	5	2	724	10	1	6	8
3	3	1	5	0	5	720	2	1	5
4	4	0	6	1	1	2	688	1	11
9	5	6	3	4	1	8	0	708	16
5	0	1	2	9	8	11	7	8	714

In ***Table 3*** classification report of the KNN model including Precision, Recall and F1-score values are shown. Digit 0 is recognized with the highest F1-score value, i.e., 0.95 whereas digit 9 has the minimum F1-score of 0.87.

Table 3. KNN Classification Report

	Precision	Recall	F1-Score	Support
0	0.95	0.95	0.95	728
1	0.93	0.94	0.94	705
2	0.94	0.92	0.93	743
3	0.89	0.93	0.91	731
4	0.92	0.90	0.91	767
5	0.91	0.91	0.92	718
6	0.94	0.91	0.93	773
7	0.92	0.93	0.93	746
8	0.89	0.90	0.89	756
9	0.87	0.87	0.87	750
Accuracy			0.92	7417
Macro Avg	0.92	0.92	0.92	7417
Weighted Avg	0.92	0.92	0.92	7417

4.2 Results for Decision Tree

The accuracy of predicting 7,417 images using Decision Tree (DT) model is 91.77%. ***Table 4*** is showing the confusion matrix of the DT model.

Table 4. Decision Tree Confusion Matrix

706	2	7	0	5	2	6	11	3	3
7	674	3	2	8	1	2	14	5	3
8	3	652	7	6	2	5	2	18	5
1	6	3	692	4	9	7	6	6	15
1	4	4	7	688	5	7	2	4	27
0	3	3	5	6	686	24	3	5	24
7	0	8	8	2	8	688	5	13	6
8	19	4	7	1	3	3	668	3	2
5	5	11	11	8	4	19	4	677	16
2	9	4	24	22	13	1	4	10	676

In ***Table 5*** the classification report of the DT model is shown. Here too, digit 0 resulted in the highest F1-score i.e., 0.95 whereas digit 9 shows the minimum F1-score of 0.88.

Table 5. Decision Tree Classification Report

	Precision	Recall	F1-Score	Support
0	0.95	0.95	0.95	745
1	0.93	0.94	0.93	719
2	0.93	0.92	0.93	708
3	0.91	0.92	0.92	749
4	0.92	0.92	0.92	749
5	0.94	0.90	0.92	759
6	0.90	0.92	0.91	745
7	0.93	0.93	0.93	718
8	0.91	0.89	0.90	760
9	0.87	0.88	0.88	765
Accuracy			0.92	7417
Macro Avg	0.92	0.92	0.92	7417
Weighted Avg	0.92	0.92	0.92	7417

4.3 Results of Support Vector Machine

SVM resulted in accuracy of 98.51% while testing the 7,417 images. ***Table 6*** shows confusion matrix of the SVM model.

Table 6. Support Vector Machine Confusion Matrix

724	0	0	0	0	0	1	3	0	0
2	691	0	0	0	0	0	11	1	0
2	0	739	1	0	0	1	0	0	0
0	0	0	729	0	0	1	0	0	1
1	0	1	2	759	1	0	0	0	3
0	1	1	0	0	710	4	0	1	1
3	0	0	1	0	7	760	0	2	0
2	9	0	1	0	0	1	731	2	0
4	1	1	3	3	1	5	0	735	3
0	1	1	7	6	3	1	0	2	729

Table 7 is showing the classification report of the SVM model. It can be seen that digits 0,2,3,4,5 resulted with the highest F1-score i.e., 0.99 whereas the remaining digits gave the same F1-score of 0.98.

4.4 Results of Random Forest

The accuracy of the RF model using the 7,417 images dataset is 53.24%. confusion matrix of the Random Forest model is shown in ***Table 8***. Classification report of the Random Forest model is shown in ***Table 9***. It can be seen that digit 0 resulted with the highest F1-

Table 7. SVM Classification Report

	Precision	Recall	F1-Score	Support
0	0.98	0.99	0.99	728
1	0.98	0.98	0.98	705
2	0.99	0.99	0.99	743
3	0.98	1.00	0.99	731
4	0.99	0.99	0.99	767
5	0.98	0.99	0.99	718
6	0.98	0.98	0.98	773
7	0.98	0.98	0.98	746
8	0.99	0.97	0.98	756
9	0.99	0.97	0.98	750
Accuracy			0.99	7417
Macro Avg	0.99	0.99	0.99	7417
Weighted Avg	0.99	0.99	0.99	7417

Table 8. Random Forest Confusion Matrix

531	44	1	2	2	0	5	0	159	1
5	544	0	0	0	0	9	7	154	0
6	2	367	65	108	0	2	0	158	0
5	2	0	414	150	0	0	0	177	1
7	0	0	5	563	0	3	1	170	0
8	4	0	111	130	330	0	0	175	1
6	1	74	0	108	59	321	0	176	0
1	91	0	0	2	0	5	466	153	0
15	3	173	0	132	80	89	0	266	2
4	3	0	160	136	137	0	1	177	147

score, i.e., 0.80 whereas digit 8 has the minimum F1-score of 0.21.

4.5 Results of Convolutional Neural Network

For CNN model testing with 5 epochs was used which are shown in ***Table 10***. CNN model achieved an accuracy of 92.62% using 7,417 images. ***Table 11*** shows the classification report of the CNN model.

5 Discussion

In this section, we summarize the performance of all trained classifiers based on their results. ***Figure 13*** shows a comparison of accuracy in the form of the bar chart of classifiers which we have used. This bar chart shows that SVM with the accuracy of 98.51% is having

Table 9. Random Forest Classification Report

	Precision	Recall	F1-Score	Support
0	0.90	0.71	0.80	745
1	0.78	0.76	0.77	719
2	0.60	0.52	0.55	708
3	0.55	0.55	0.55	749
4	0.42	0.75	0.54	749
5	0.54	0.43	0.48	759
6	0.74	0.43	0.54	745
7	0.98	0.65	0.78	718
8	0.15	0.35	0.21	760
9	0.97	0.19	0.32	765
Accuracy			0.53	7417
Macro Avg	0.66	0.53	0.56	7417
Weighted Avg	0.66	0.53	0.55	7417

Table 10. Training and Validation Metrics across Epochs

Epoch	Time	Loss	Accuracy	Val Loss	Val Accuracy
1/5	12s 35ms	1.0422	0.6266	0.5758	0.7866
2/5	11s 35ms	0.4623	0.8375	0.3488	0.8670
3/5	12s 37ms	0.3199	0.8890	0.2283	0.9236
4/5	12s 36ms	0.2274	0.9196	0.1804	0.9358
5/5	12s 37ms	0.1761	0.9353	0.1880	0.9272

the best result and random forest with accuracy of 53.24% is having worst accuracy.

Figure 14 presents a bar chart displaying the precision and recall for all four ML classifiers. It can be observed that SVM achieved the highest precision and recall, with 98% and 99%, respectively. In contrast, RF resulted in the lowest precision and **??** recall, with 90% and 71%, respectively. represents the accuracy, precision and recall of each classifier used in this research.

Table 11. Training and Validation Metrics across Epochs

Classifier	Accuracy	Precision	Recall	F1 Score
SVM	98.51%	99%	99%	99%
KNN	91.1%	92%	92%	92%
Decision Tree	91.77%	92%	92%	92%
Random Forest	53.22%	66%	53%	56%
CNN	92.65%	92%	92%	92%

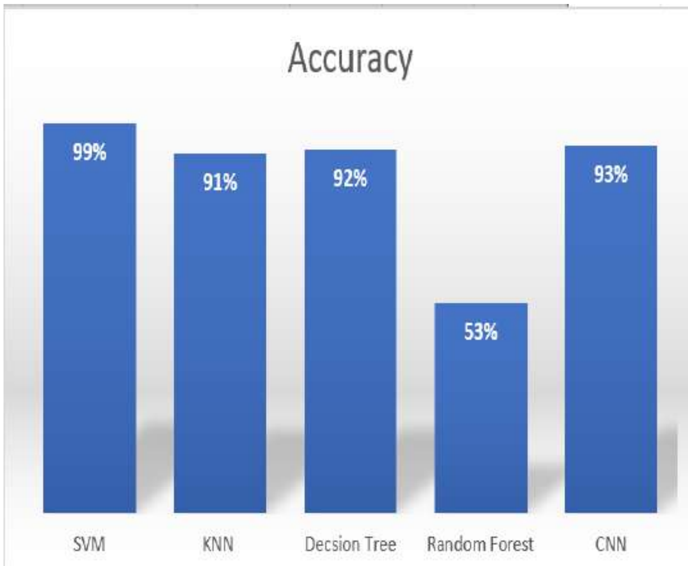

Figure 13. Classifiers Accuracy Comparison

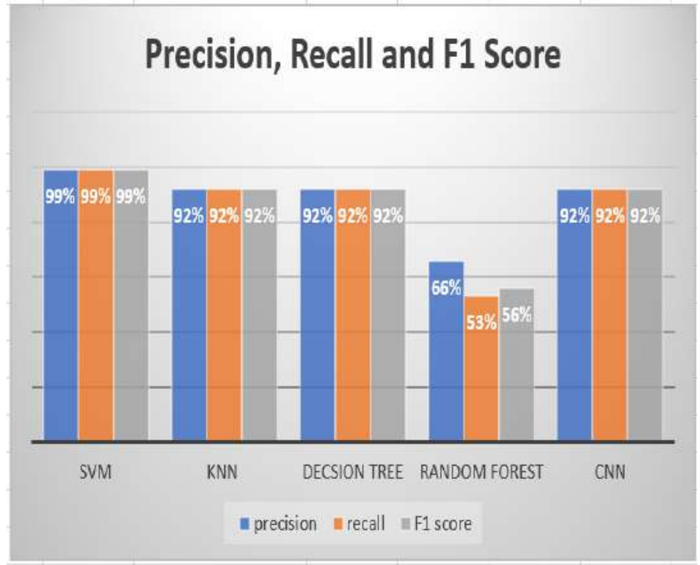

Figure 14. Precision and Recall for ML Classifiers

6 Conclusion

Digital electrical meters are installed in Pakistan which monitor the electricity usage (units) provided to houses, industries, hospitals, and everywhere. Readings of these meters are taken manually by capturing the images. Meter readers capture images using mobile phone cameras. A person then reads these images one by one, calculates the units consumed, and uses this information to calculate the electricity bills. The captured images contain noise, blurriness, shadows, poor contrast, and tilting, making it more challenging to accurately recognize digits. This process is lengthy and time-consuming. As technology is growing rapidly, this process should be automated as much as possible to save our time, cost, and effort. This research aims to make a system that can read these images automatically and help in improving the billing system by saving time and effort.

For this purpose, a dataset of 494 manually captured electric meter images has been used to train 5 different supervised learning models for digit recognition. The reason for using multiple models is to determine which ones provide better accuracy for this type of dataset. The models trained in this research include K-nearest neighbor, Decision Tree, Support vector Machine, Random Forest, and Convolutional Neural Network. This research reveals that the Support Vector Machine is the most suitable model for this dataset which gives 98.51% accuracy and the worst model for this dataset is a random forest which gives 53.24%. Other models are also giving reasonably good results. The K-nearest neighbor gives 95.22% accuracy, Decision tree gives 91.77% accuracy, and the CNN model gives 92.65% accuracy.

7 Future work

This research can be considered as a step towards automating the electric billing system in Pakistan. Once we can recognize the digits, we can make a system which can automate the process of calculating units and generating the bills. In future, more experiments can be performed on other types of meters, including other utility services meters water and gas. Dataset can be extended to enable training of advanced deep learning models that require large training data.

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

Author Contributions

Hamza Haseeb: Idea, Methodology, Writing- Original draft preparation **Malik Tahir Hassan**: Software, Validation **Afnan Iftikhar**: Analysis , Supervision **Ayesha Asmat**: Simulation work.

References

[1] N. Cameron, *7-Segment LED Display: Comprehensive Projects for Everyday Electronics*. Springer, 2019.

[2] T. Kasar, *Recognition of Seven-Segment Displays from Images of Digital Energy Meters*, pp. 1–10. Singapore: Springer, 2019.

[3] K. Kanagarathinam and K. Sekar, "Text detection and recognition in raw image dataset of seven-segment digital energy meter display," *Energy Reports*, vol. 5, no. 11, pp. 842–852, 2019.

[4] "Yuva eb dataset - google drive." https://drive.google.com/drive/folders/1J9TYUiLKdJKfSeotL-_ElyvXQ-3pE282. Accessed: Jul. 09, 2024.

[5] K. Gushima and T. Kashima, "Automatic generation of seven-segment display image for machine-learning-based digital meter reading," in *PHM Society Asia-Pacific Conference*, 2023. Accessed: Jul. 09, 2024.

[6] A. K. Sharma and K. K. Kim, "Lightweight cnn based meter digit recognition," *Journal of Sensor Science and Technology*, vol. 30, no. 1, pp. 15–19, 2021.

[7] L. M. Low, F. H. M. Salleh, Y. F. Law, and N. Z. Zakaria, "Detecting and recognizing seven-segment digits using a deep learning approach," *ITM Web of Conferences*, vol. 63, no. 1, p. 01007, 2024.

[8] "Medium-sized seven-segment digital tube data set_dataset-paddlepaddle ai studio galaxy community." Accessed: Jul. 10, 2024.

[9] E. Finnegan, M. Villarroel, C. Velardo, and L. Tarassenko, "Automated method for detecting and reading seven-segment digits from images of blood glucose metres and blood pressure monitors," *Journal of Medical Engineering and Technology*, vol. 43, no. 6, pp. 341–355, 2019.

[10] N. Boonsim and S. Kanjaruek, "An integrated technique for detecting seven-segment digits on medical devices," in *2023 27th International Computer Science and Engineering Conference (ICSEC)*, pp. 1–4, IEEE, 2023. Accessed: Jul. 10, 2024.

[11] M. Rahman, M. R. Al Islam, M. D. Rezyuan, and M. S. Islam, "Smart health care monitoring system by seven segment image processing technique," in *2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, pp. 1–6, IEEE, 2019. Accessed: Jul. 10, 2024.

[12] V. N. Shenoy and O. O. Aalami, "Utilizing smartphone-based machine learning in medical monitor data collection: Seven segment digit recognition," in *AMIA Annual Symposium Proceedings*, p. 1564, American Medical Informatics Association, 2017. Accessed: Jul. 10, 2024.

[13] H. Marais, "Automatic extraction of data from infra-red thermometers with computer vision," *IFAC-PapersOnLine*, vol. 56, pp. 7038–7043, Jan 2023.

[14] S. Jeon, B. S. Ko, and S. H. Son, "Romi: A real-time optical digit recognition embedded system for monitoring patients in intensive care units," *Sensors*, vol. 23, no. 2, p. 638, 2023.

[15] J. Peng, W. Zhou, Y. Han, M. Li, and W. Liu, "Deep learning-based autonomous real-time digital meter reading recognition method for natural scenes," *Measurement*, vol. 222, p. 113615, Nov 2023.

[16] M. Imran, H. Anwar, M. Tufail, A. Khan, M. Khan, and D. A. Ramli, "Image-based automatic energy meter reading using deep learning," *Computers, Materials & Continua*, vol. 74, no. 1, pp. 203–216, 2023.

[17] E. A. Enriquez, N. Gordillo, L. M. Bergasa, E. Romera, and C. G. Huélamo, *Convolutional Neural Network vs Traditional Methods for Offline Recognition of Handwritten Digits*, pp. 87–99. Cham: Springer International Publishing, 2019.

[18] P. Ganesan and G. Sajiv, "A comprehensive study of edge detection for image processing applications," in *2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS)*, pp. 1–6, Mar 2017.

[19] Vipin, "Contour detection in opencv: A comprehensive guide," 2024. Accessed: Jul. 05, 2024.

[20] O. Kramer, *K-Nearest Neighbors*, pp. 13–23. Berlin, Heidelberg: Springer, 2013.

[21] L. Rokach and O. Maimon, *Decision Trees*, pp. 165–192. Boston, MA: Springer, 2005.

[22] L. Wang, *Support Vector Machines: Theory and Applications*. Springer Science & Business Media, 2005.

[23] A. Paul, D. P. Mukherjee, P. Das, A. Gangopadhyay, A. R. Chintha, and S. Kundu, “Improved random forest for classification,” *IEEE Trans. Image Process.*, vol. 27, pp. 4012–4024, Aug 2018.