REVIEW OF MACHINE LEARNING TECHNIQUES FOR HANDWRITTEN CHARACTER RECOGNITION

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Abstract: Optical Character Recognition (OCR) of handwritten text is still a challenging research area due to different writing styles of different individuals. Character recognition helps in extracting important and required text from a document. The difficulty in handwritten character recognition is due to different individual writing styles and diacritics in some languages like Yoruba which lead to tonal difference in their text making handwritten recognition system a complex system. To overcome this challenge, researchers are carrying out researches to discover better ways of developing automated character recognition systems with excellent recognition accuracy. This study aims to review the work on computer vision regarding character recognition in the last seventeen years. Over 52 publications on OCR of handwritten documents are extracted from science direct, google and scopus databases. Review of Machine Learning techniques for handwritten character recognition is presented. Machine learning methods used for classification in OCR used to achieve better results are also presented. The Literature review presented in this study reveals importance of OCR in areas such as automated library and office documents, bank check processing, banking services, postal services, and health service and in museum for National archives for digital searchable storage of historical text and shows that perfect OCR system is a difficult and challenging research area in terms of handwritten character recognition. This study would provide knowledge and creation of perfect character recognition systems and guide researchers and expert in future research.

Keywords: Character, Handwritten, Machine Learning, Optical, Recognition, Techniques

Introduction

Artificial Intelligence (AI) is the science of imitating human mental abilities in a computer (Akrimi et al., 2015) including reasoning, understanding, imagination, recognition, emotions and creativity. AI offers a wide range of techniques that allow computers to solve tasks requiring human skills such as problem solving. Application areas of AI include information processing, computer gaming, national security, computer vision, speech recognition, e-commerce, healthcare, transport, finance, data security, education, agriculture and entertainment.

Machine Learning (ML) is a subfield of AI which combines data with statistical tools to predict any output which can be used to make a decision. ML focuses on designing algorithms that are able to learn from data without being explicitly programmed to perform a task (Bansal et al., 2020). ML has been used in areas such as fraud detection, object detection, object segmentation and character recognition.

Deep learning is a subfield of ML which tries to learn or extract information in data by utilizing hierarchical architecture (Guo et al., 2015). Several deep learning approaches or algorithms have been developed to solve AI problems. Deep learning finds application in computer vision tasks such as object detection image, classification and image retrieval. Lower cost of computing hardware and increased in Chip processing abilities contribute to the current popularity of deep learning. Researches in deep learning resulted to a large number of approaches.

Optical Character Recognition (OCR) is electronic conversion of images of printed or handwritten document into editable and searchable text (Chandio et al., 2020). OCR uses computer vision and artificial intelligence techniques to study limited set of characters to recognize unlimited set of such characters. Handwritten character recognition is grouped into online and offline handwritten character recognition depending on how data is acquired (Goswami et al., 2013). Offline data is usually collected using pen and paper before scanning into electronic form as images while online data are obtained directly using a digitizer and an electric pen (Ojumah et al., 2018). Machine printed character recognition is usually offline character recognition because data is mostly acquired from scanned images of document to be recognized. OCR of handwritten documents is still a challenging research area due to variable writing style of individuals (Pareek et al., 2020).

This research focuses on the review of various ML techniques and major steps used for recognition of handwritten text so as to complement the existing surveys in literature. Other aspects of this research paper are; section 1 presents introduction. Section 2 provides methodology for systematic review of selected articles used in this study. A review of the major step used in character recognition system is presented in section 3. Section 4 discussed review of while section 5 conclude and recommend future researches.

Methodology

This section presents methodology for systematic review of selected articles used in this research. Published papers on handwritten character recognition over the past seventeen years were searched and analyzed. Reviewing these works will provide a new direction in the field of computer vision as regards to handwritten character recognition. Publications relating to character recognition were searched from scopus, google and science direct databases from year 2005 to year 2022. This was done to find out potential research gaps in the field of computer vision and help to get updated with activities regarding publication trends. Keywords used for collection of data are **optical character recognition, machine learning, deep learning, artificial intelligence and handwritten character recognition.**

Review of Major Steps used in Character Recognition System

The following steps are the common methodology used for OCR by most researchers. The stages are divided into five namely; image acquisition or data acquisition, image preprocessing, and image segmentation, feature extraction and classification and performance evaluation. Figure 1 shows the framework of handwritten character recognition system.

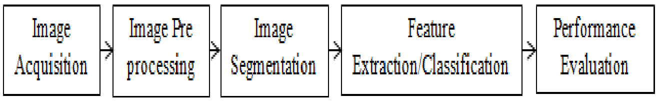

Figure 1: Framework of Handwritten Character Recognition System

Image Acquisition

The first step in character recognition is image acquisition. Images are usually captured by a scanner or digital camera that uses or incorporate light sensitive devices. Character images could be machine printed or handwritten depending on the source of the image (Adeyanju et al., 2014). It is best to use good optical scanner as image of the original document is captured. Data can be acquired either locally or from open-access (publicly available which can be downloaded from Kaggle and github dataset)

Image Preprocessing

Image preprocessing is the second step in character recognition. This step is necessary in image processing in order to improve image quality and achieve good recognition accuracy (Rani, 2017). Several techniques are available and are in used. They include thinning, de-noising, Grayscale conversion, colour space conversion, image resizing and cropping. These are used to improve image quality and solve the problem of space complexity.

Cropping

This preprocessing technique is used to remove unnecessary features from an image. The purpose of this stage in image preprocessing is to remove irrelevant pixels for better representation (Demilew and Sekeroglu, 2019). Cropping is done to remove unnecessary features such as background leaving only the relevant features. Figure 2 shows a sample of cropped image.

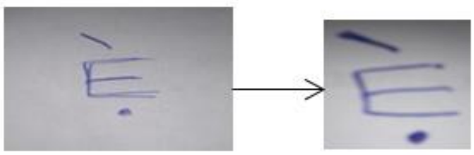

Figure 2: Sample of a cropped Yoruba character image with diacritic (Adapted from Oladele et al., 2017)

Noise Removal

Noise removal involves removing noise from an image. This process of removing unwanted features from images needs to be done in a careful manner so as not to remove useful parts or features of the image. This will help to remove noise from images. The different types of noise that is found in digital images include salt and pepper noise, mixed noise, Gaussian noise, gamma noise and union noise (Mohan and Jyothi, 2015). Salt and pepper noise also called impulse noise result into white and black spots in images. This is why it is called Salt (white) and pepper (black) noise. Mixed noise is as a result of different types of noise in images. Gaussian noise is an additive noise and happens during image acquisition process. Image filter is used to remove noise from digital image. Image filter transform images using different filtering techniques. Filtering techniques that are used to filter or remove noise include mean filter, median filter and Gaussian filter.

Image Resizing

Original digital images are in RGB (Red, Green and Blue) jpg format. Images used in OCR are usually resized to uniform sizes such as 16×16, 32×32 and 72×72 pixels to have uniform images. This is necessary due to square shape (fixed size) of dataset used by some machine learning models.

Grayscale Conversion

A grayscale image is a scale of shades from black to white used in digital image technology. Grayscale images have many shades of Gray in between (Buyuksahin, 2014). This convert the origin RGB images into grayscale images for further processing so as to reduce memory space consumed by RGB images. An image is represented by its dimension based on the number of pixels. An image with dimension 500x500, has 250000 pixels.

Image Segmentation

The next stage after image preprocessing is image segmentation. Segmentation also known as partitioning is the process of partitioning an image into different regions for the purpose of image analysis (Sumithra et al., 2015). It also means partitioning of images into various regions or parts (Rani, 2017). Three steps are involved in segmentation. These include; line segmentation, which divides the characters in image horizontally; word segmentation, which divides words from line sentence and character segmentation, which divides the character from words.

The Methods of image segmentation include thresholding, colour based, transform method, texture method, clustering and edge based. Image segmentation can be grouped into two types (Shivhare and Gupta, 2015); local and global segmentation. Global partitioning is partitioning of a whole image. Figure 3 shows the various image segmentation methods.

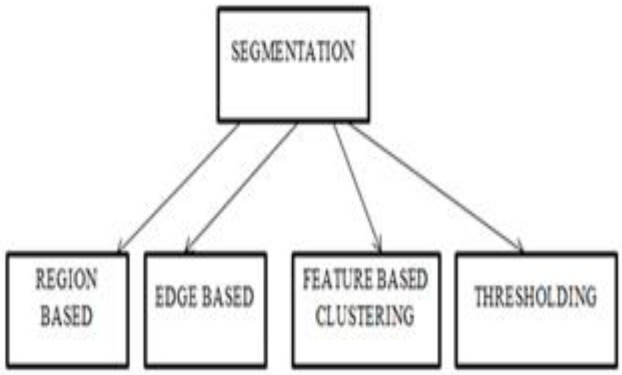

Figure 3: Various image segmentation techniques (Adapted from Rani, 2017)

Region Based Segmentation

For region based segmentation method, region of interests is isolated from the rest of the image. Region based segmentation divides image into regions or parts that are similar according to a set of predefined rule. This technique relies on common patterns in intensity values within a cluster of neighbouring pixels (Saini and Arora, 2014). Region based segmentation technique is a method that partition image into different regions having same characteristics.

Edge Based Segmentation

Boundary or edge based method is used for detecting discontinuities in gray level images. This transforms images into edge images benefitting from the changes of grey tones in the images (Senthilkumaran and Rajesh, 2009).

Feature Based Clustering

In this segmentation technique, images are transformed into Histogram. Clustering is performed on the transform histogram. Pixels of the coloured images are clustered for segmentation (Rani, 2017). The two basic types of clustering are soft and hard clustering. Hard clustering divides image into set of clusters while soft clustering is used for image segmentation in which division is not strict and the pixels are partitioned into clusters that are based on partial membership (Kaur and Kaur, 2014; Zhang, 2006). This means one pixel can belong to more than one clusters.

Thresholding

Thresholding is an image segmentation method. Thresholding is used to convert grayscale to binary image. Binary images are images produced from coloured images by segmentation. The conversion of coloured or grayscale image into binary image using thresholding is referred to as binarization. It help to get a value called threshold value that separate the foreground of the image from background so as to reduce the overlapping that occurs between the two pixels (black and white pixels) (Demilew and Sekeroglu, 2019). Figure 4 shows binarized image. Threshold technique is defined by Kaur and Kaur (2014) as;

$$\text{g (x,y)} = f(x) = \begin{cases} 1 \ if\ (x,y) \geq T \\ 0\ otherwise \end{cases} \quad (1)$$

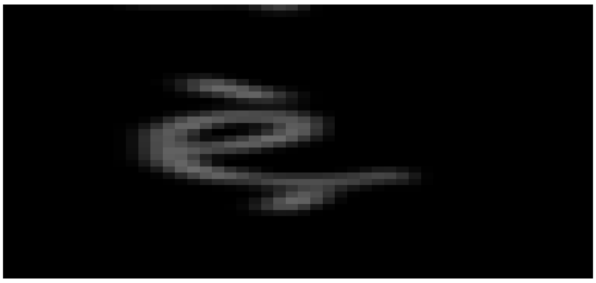

Figure 4: Picture of Binarized Handwritten image

Feature Extraction Techniques

After the completion of image segmentation, the next stage is feature extraction and classification. The features extracted play an important role in recognition accuracy, training speed, testing speed and computation time. Feature extraction involves the removal of unnecessary information from input image and extracting the important features for classification. The extracted features play important role in recognition accuracy. The main aim of feature extraction is to acquire the needed information from the original image (Kumar and Bhatia, 2014). The more we are able to extract features from images (characters), the better we can perform character recognition in the highest accuracy. A good feature extraction technique provides relevant features (Medjahed, 2015). Common feature extraction techniques used in OCR include geometric and topological (structural) features extraction, statistical feature extraction and global transformation and series expansion techniques.

Geometric Feature Extraction Techniques

Geometric feature extraction technique is also known as structural features extraction. Geometric features are based on the basic line types that form the character skeletons (Pithadia and Nimavat, 2015). Structural features are based on geometrical and topological properties of an image such as character which include lines, curves, loops and T-points (Mohan and Jyothi, 2015). Final Feature vectors are obtained from this technique. Geometrical feature technique extracts geometric features of images.

Statistical Feature Extraction Technique

This is a statistical method of examining and representing the textures of images by considering the spatial relationship of the pixels. Statistical features represent the character image as statistical distribution of points. Statistical Feature extraction techniques includes zoning, projection, graph matching and border transition techniques. Zoning involves the division of a character image into smaller fragment of area. The frame in which the frame is located is divided into several non-overlapping zones. In this method, the black pixels in each zone are counted and the total accumulated profiles in each zone extract the feature of the character (Pithadia and Nimavat, 2015). In projection method, data is compare through projection. Character may be represented by projecting pixel gray values on lines in different directions. Graph matching method uses structural features of character such as branch points, end points and curve points. Three features are defined here. They include the end points, branch points and curve points. The end point is connected to only one pixel which contains information of positions. Curve point is connected to only two pixels and branch point is connected to more three pixels which is having feature information connected to the branch point. Straight line is also connected to two pixels as well. Information includes position and detection which are also called features. Direction information is used to differentiate a curve from a straight line. Figures 5 and 6 illustrate zoning and graph matching method of feature extraction of character images.

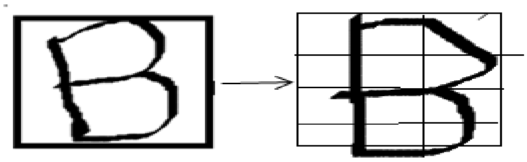

Figure 5: Zoning of character image (Adapted from Pithadia and Nimavat, 2015)

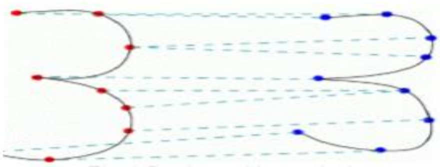

Figure 6: Graph matching method (Pithadia and Nimavat, 2015)

Global Transformation and Series Expansion Techniques

Common transformation and series expansion methods used in OCR include wavelets, fourier descriptor; moment and gabor transform (AshlinDeepa and RajeswaraRao, 2014). Fourier transform is used for shape analysis to determine fourier coefficient and pixel brightness so that shape features can be computed. Moment based feature is a technique of feature extraction that is very effective in shapes Analysis that is describing Shape of characters.

Machine Learning Algorithms for Handwritten Character Recognition

After the preprocessing, segmentation and feature extraction, the next step is classification. Machine learning algorithms are used for classification to give meaning to the extracted image features. Machine learning algorithms used for character recognition include K-nearest Neighbour (KNN), Support Vector Machine (SVM), Hidden Markov Model (HMM), Artificial Neural Network (ANN) and deep learning approaches (Mohan and Jyothi, 2015; Sarker, 2021). K-Nearest Neighbour (KNN) is a kind of instanced –based learning where the function is only locally estimated and all computation is referred to the nearest until classification is done. It is a lazy learning. SVM is a supervised learning algorithm that is non-probabilistic and used to solve classification problems. SVM is a binary classifier which tries to classify dataset by finding an optimal hyper plan (Medjahed, 2015). Hidden Markov Model (HMM) is a machine learning algorithm named after Russian mathematician Andrey Markov (Pietrzykowski and Salabun, 2014) who developed much of the relevant statistical theory. In HMM, the model is assumed to be a process with unknown parameters so as to determine the hidden parameters from the observable parameters (Odumuyiwa and Osisiogu, 2019). HMMs have varieties of mathematical structure that when applied appropriately perform well in practice for many application areas. HMM finds application in areas such as speech recognition, bioinformatics and handwritten recognition. Artificial Neural Network (ANN) is a computational model which is based on the working principle of human brain, which is Dendron and neuron. They are composed of many nodes which imitate biological neurons of human brain (Nayak et al., 2015). ANN is a network of interconnecting processing element working in parallel. Another group of processing element is called a layer in the network. The first layer is called the input layer while the last layer is the output layer. There is an additional layer of units called hidden layer(s). A Neural network can be train to perform a particular function by altering the weight values. This helps to build predictive model from large dataset and are used in pattern recognition and classification. CNN is one of the most commonly used deep learning models where multiple layers are trained (Guo et al., 2015). It is an effective algorithm and most commonly used in diverse computer vision applications such as object detection and pattern recognition. CNN is made up of three main neural layers namely; convolutional layers, pooling layers, and fully connected layers. Each of these layers has their various roles. CNN has emerged as a popular technique used for classification based on contextual information and has immense ability to learn contextual features (Sakshi Indolia et al., 2018). CNN reduces number of parameters required to a great extent as it extracts features itself. It is extensively used for solving classification problems.

Performance Evaluation

Performance evaluation is used to measure the performance of a system. The performance evaluation metrics used to measure the performance of character recognition system include recognition accuracy in percentage, segmentation accuracy in percentage, character-level recognition accuracy in percentage and testing time in seconds.

(i) Accuracy: This measures the overall effectiveness of the developed system and it is measured in percentage (%). Two types of accuracy used to evaluate the performance of character recognition system are;

(a) Segmentation accuracy: This measures the segmentation accuracy of the system in terms of how the words were segmented into individual character. It is measured in percentage (%) and given as;

Segmentation Accuracy =

$$\frac{Number\ of\ Correcly\ segmented\ characters}{Total\ number\ of\ characters\ in\ the\ word} \quad (2)$$

(b) Character-Level Recognition Accuracy: This measures the recognition accuracy of the system in terms of recognition of individual character in a word. It is measured in percentage (%) and given as;

Character-Level Recognition Accuracy

$$= \frac{Number\ of\ correctly\ classified\ characters}{Total\ number\ of\ characters\ in\ the\ word} \quad (3)$$

(ii) Testing time: This determines the average time taken to classify word images by the developed system and it is calculated in seconds (s). Average testing time is calculated by dividing the total testing time with the number of testing dataset.

Evaluation methods used to evaluate the performance of character recognition system is hold-out and cross validation. Hold-out is just dividing the whole dataset into training and testing data. The split is used once without repetition of changed split. For hold-out method, a large portion of the dataset is used for training and validation set while the remaining portion is used for testing. Cross validation is a technique used in machine learning to evaluate the performance of a model on unseen data. It involves dividing the available data into multiples folds or subsets, using one of these folds as a validation set and training the model on the remaining folds. This process is repeated multiple times, each time using a different fold as the validation set. Finally, the results from each validation step are averaged to produce a more robust estimate of the model's performance. Cross validation is an important step in the machine learning process and helps to ensure that the model selected for deployment is robust and generalized well to new data.

Review of Machine Learning Techniques Used in Handwritten Character Recognition

Machine learning algorithms used for classification and recognition of handwritten character include KNN, SVM, HMM, ANN and Deep learning approach (Sarker, 2021). Literature review classified machine learning algorithms into machine learning and deep learning. Machine learning algorithms include KNN, SVM, HMM and ANN. Deep learning algorithms include Convolutional Neural Network, Restricted Boltzmann Machines, Auto encoder and sparse coding methods. Literature review shows that the common machine learning methods used for character recognition is SVM while deep learning approach commonly used is CNN. Figure 7 illustrate the categories of deep learning methods

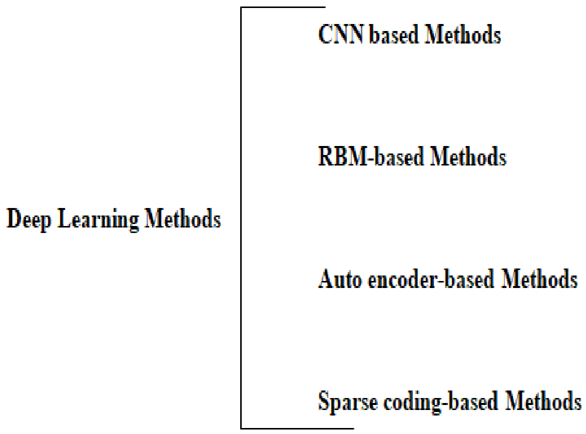

Figure 7: Classification of deep learning methods (Adapted from Guo et al., 2015)

Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning technique used for classification problems. SVM is a binary classifier which tries to classify dataset by finding an optimal hyper plan (Medjahed, 2015). Many variant of SVM methods have been developed to overcome the problem of hyper parameters. They include SVM-SMO, LS-SVM and u-SVM. It is effective in high –dimensional space and can behave differently based on different mathematical functions known as Kernel (Sarker, 2021). Kernel functions used in SVM classifier include sigmoid, linear, polynomial and Radial Basis Function (RBF).

Kumar et al. (2012) developed a handwritten character recognition using Support Vector Machine (SVM) classifier and MLP Neural Network. The linear kernel function used in SVM recorded the highest recognition accuracy of 94.8% outperforming the neural network. Narang et al. (2019) developed Devanagari ancient documents recognition system. The system achieved 88.95%. Oladele et al. (2017) developed an offline character recognition system using SVM as a classifier to recognize Yoruba alphabets. A recognition accuracy of 76.7% was obtained. Fenwa et al. (2012) proposed online character recognition using a hybrid feature extraction algorithm. The research was able to developed a feature extraction technique for online character recognition system. Nasien et al. (2010) developed SVM classifier for character recognition for English handwritten character recognition. The proposed model reached a relatively high accuracy. Oladele et al. (2020) developed handwritten word recognition system that uses geometric feature extraction techniques and a SVM classifier. The recognition accuracy ranges between 66.7% and 100%. The words used in the system vary from four to seven letters word. Twenty different words were used. The system can only recognize upper case Yoruba letters

Convolutional Neural Networks

The Convolutional Neural Networks (CNN) is one of the most commonly used deep learning approaches where multiple layers are trained in a robust manner (Guo et al., 2015). It is an effective algorithm and most commonly used in diverse computer vision applications such as object detection and pattern recognition.

CNN is a technique used for classification and has ability to learn features from images (Sakshi et al., 2018). CNN is used for classification problems. Figure 8 shows architecture of LeNet5, a variant of CNN.

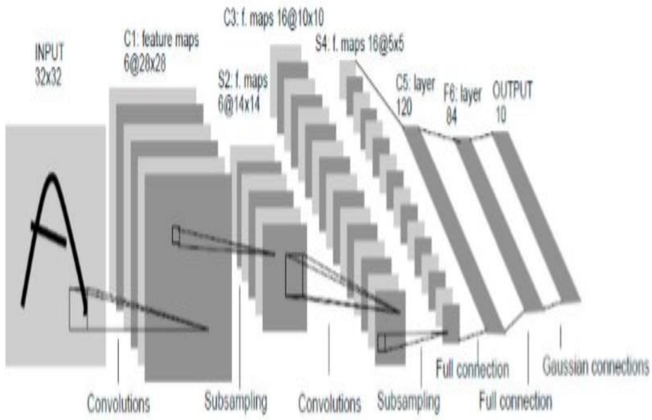

Figure 8: Architecture of LeNet5, a CNN where each box represents a different feature map (Sakshi et al., 2018)

Goltsev and Rachkovskij (2005) developed recognition for handwritten digits arranged in numeral strings by combining assembly neural network with a perceptron. The experiment showed that the system was able to correctly recognized digits of the MNIST test set. Kluzner (2009) developed a word-based Adaptive Optical Character Recognition for historical books using word image comparison algorithm which is split into two stages. Jangid and Srivastava (2018) developed handwritten character recognition for Denanagari using layer deep CNN. The database obtained 98% accuracy. Narang et al. (2021) presented character recognition system for Devanagari language using Convolutional neural network. The developed system achieved a recognition accuracy of 93.73%. The character dataset was restricted only to 33 basic characters.

Rani et al. (2018) proposed a deformed character recognition system using CNN for handwritten Kannada characters. The developed system obtained 87% recognition accuracy for printed character sample and 80% for handwritten text with respect to handwritten data. Madakannu and Selvaraj (2019) developed a deep CNN for multi-format digit recognition system. The developed system obtained recognition accuracy of 93.29%, 97.60% and 99.11% for the three dataset used. Ahamed et al. (2020) developed a handwritten Arabic numerals recognition system using CNN to create a handwritten Arabic numerals dataset. The developed architecture produced 99.76% recognition accuracy.

Sujata and Verma (2019) developed character recognition system using deep CNN to recognize Japanese historical script. MNIST dataset achieved an accuracy of 99.47%. The average accuracy of the proposed model on four dataset was 96.55%. Naseer et al. (2020) proposed character recognition system for Balochi using Deep Neural Network for Balochi script recognition for non-cursive characters. The system was compared with the LeNet model and the results showed a precision of 96%.
Sujatha and Bhaskari (2019) proposed a Telugu and Hindi script recognition system using deep learning technique for recognition of Telugu and Hindi language. Features were extracted using CNN and deep neural network. The system achieved classification accuracy of 92.4% using CNN for Telugu character while that of CNN-Random forest, CNN-Multilayer Perceptron and CNN-KNN achieved classification accuracy of 71.4%, 77.5% and 81.6% respectively. Bisht and Gupta (2020) proposed a Devanagari character recognition using CNN. The CNN model performed best compare to all previous method developed for Devanagari handwritten

character recognition for both character and numeral recognition together for large dataset. However, it does not work well for degraded documents.

Demilew and Sekeroglu (2019) developed an ancient Geez script recognition system using deep learning to recognize twenty six characters of Ethiopian ancient Geez alphabets. Preprocessing was done. The proposed system achieved recognition accuracy of 99.39%. Kadir et al. (2019) evaluated the recognition performance of CNN and bag of features for multi-font digit recognition. The recognition accuracy produced by CNN was 96% while that of BoF was 94%. Khan et al. (2021) proposed Bangla handwritten compound character recognition system to recognize Bangla handwritten character using CNN. The result demonstrated an average frequency of 99.82% in recognizing Bangla handwritten compound characters using Mendeley Bangla Lekha-isolated 2 dataset. Mustafa and Elbashir (2020) proposed a deep learning model for handwritten Arabic names recognition system to recognize Arabic names by down scaling the image to 28x56 pixels and using CNN as a classifier. The accuracy was 99.14%.

Oyeniran and Oyebode (2021a) presented Yorùbá alphabets recognition system using deep learning. The accuracy of the system was 97.97%. The proposed system was able to only recognized Yoruba alphabets. It did not consider Yoruba words

Lukasik et al. (2021) proposed character recognition system for handwritten Latin characters using CNN. The developed architecture recorded an accuracy of 96%. The research was conducted for digits; upper case Latin letters, upper case Latin letters with diacritics, upper case all characters (digits, uppercase Latin, upper case Latin letters with diacritics and special characters (lower and upper case).

Oyeniran and Oyebode (2021b) developed a handwritten character recognition system for Yoruba language using AlexNet, a deep learning model. The recognition accuracy of the developed system was recorded to be 91.4%. However, the system was unable to recognize the alphabets ‘**Ṣ’** and ‘**ṣ’** with recognition accuracy of 0%.

Sonara and Pandi (2021) proposed Handwritten Character Recognition using Convolutional Neural Networks. Preprocessing techniques used include noise removal using median filter, grayscale conversion and image thinning. Segmentation was done using character segmentation and Convolutional Neural Network was used as classifier. The system achieved 95% recognition accuracy using English Handwritten characters. The research is only limited to English characters. Kala (2022) proposed Handwritten Character Recognition using Neural Networks for Hindi, Telgu, Kannada, Malayam and English. Preprocessing processes used were noise removal, skew detection and correction and binarization. Three types of segmentation were used (lines, word and characters segmentation). Classification was done using Convolutional Neural Networks. However, one language can be recognized at a time. Tables 1 and 2 summarized reviewed machine learning methods in character recognition and advantages and disadvantages of SVM and CNN classifiers respectively. The research gaps and challenges for current handwritten character recognition include limited character recognition, high computational cost and time.

Table 1: Summary of Some Selected Reviewed Machine Learning Methods in Character Recognition Systems

Authors	**Preprocessing**	**Segmentation**	**Feature Extraction**	**Classification/Recognition**	**Accuracy**	**Remark**
Oladele et al., 2017	Gray scale conversion, image filtering, edge detection, binary image conversion, image dilation and image filling	Image segmentation and character segmentation	Statistical feature extraction techniques was used(zoning,pro Jection and profiles, crossing and distances)	Support Vector Machine	76.7%	Recognize only twenty four upper case Yoruba alphabets
Oladele et al., 2020	Gray scale conversion, binari noise removal, cropping and resizing, zatio segmentation, skeletonization)	-	Geometric features extraction techniques	Support Vector Machine	Ranges between 66.7% and 100%	Twenty selected words(vary between four and seven letters)
-	-	-	-	-	-	-
Oyeniran and Oyebode, 2021a	Noise removal(median filter algorithm), resizing(227x227x3)	-	-	AlexNet	91.4%	Was unable to recognize ‘Ṣ’ and ‘ṣ’
Oyeniran and Oyebode, 2021b	-	-	Geometric feature (Zoning and gradient feature	Deep Convolutional Neural (Networks (YORUBA NET)	97.97%	Recognition Of Yoruba alphabets. Cannot recognize word images.

Table 2: Merits and Demerits of SVM and CNN Classifiers

Handwritten Recognition Classifier	Merits	Demerits
Support Vector Machine (SVM)	SVM perform well with multidimensions and continuous features. Applicable in numerous areas. Tolerance to irrelevant attributes	SVM needs a large dataset to have high prediction accuracy. Hyper parameters are always challenging while interpreting their impact.
Convolutional Neural Network (CNN)	It automatically detects important features	It has high computational cost. CNN needs

	without any human supervision. It handle image classification with high accuracy	large training data to achieve good accuracy.

Conclusions and Recommendations

This paper presents a review on various types of ML techniques and major steps used in OCR related studies from 2005 to 2022. The research trend related to handwritten character recognition is presented based on over 50 research articles collected from google, science direct and scopus databases. This work gives an overview of previous machine learning techniques used by different research over the last seventeen years on handwritten character recognition to obtain recognition accuracy. From the research works reviewed in this paper, we can understand that ML and feature extraction techniques should be chosen according to the characters you are working with due to the nature of each character or alphabet. The study established current handwritten challenges facing handwritten character recognition such as limited character recognition, high computational cost and time. The better we are able to extract features from characters, the more we can detect and recognize characters in highest accuracy. Deep Learning approaches usually extract features by themselves for classification. Unlike Deep Learning, ML techniques need features extracted by feature extraction techniques for prediction and classification. From our findings, Deep Learning approaches offer good recognition accuracy.

From our findings during this work, the following are recommended for future work; further research should be extended to combination of ML and deep learning techniques. Other deep learning approaches like Vision Transformers should be implemented as literature review shows Vision transformer models perform quite well relative to popular CNN variants on image classification task.

Conflict of Interest

There was no conflict of interest

References

Adeyanju, I.A, Fenwa, O. D., & Omidiora E.O. (2014). Effect of non-image features on recognition of handwritten alpha-numeric characters. *International Journal of Computers and Technology, 13(11*), 5155-5161.

Ahamed, P., Kundu, S., Khan, T., Bhateja, V., Sarkar, R., & Mollah, A.F. (2020). Handwritten Arabic numerals recognition using convolutional neural network. *Journal of Ambient Intelligence and Humanized Computing*, *3(4*), 1-10

Akrimi, J.A, Ahmad, A.R, George, L.E., & Aziz, S. (2015). Review of artificial intelligence. *International journal of science and research*, *2(2),* 487-505

AshlinDeepa, R. N. & RajeswaraRao, R. (2014). Feature extraction Techniques for recognition of Malayalam Handwritten characters: Review. *International Journal of Advanced trends Computer Science and Engineering,* 3(1), 481-485.

Bansal, R., Singh, J. & Kaur, R. (2020). Machine Learning and its Application: A Review. *Journal of Applied Sciences and Computations, 6(6),* 1392-1398.

Bisht, M. & Gupta, R. (2020). Multiclass recognition of offline handwritten Devanagari using CNN. *International Journal of Mathematics, Engineering and Management Sciences,*5(6), 1429- 1439

Buyuksahin, U. (2014). Vision-Based Sensor Technologies-Webcam: A Multifunction Sensor. *Comprehensive Materials Processing, 13,* 375-392. Doi:10.1016/b978-0-08-096532- 1.01314-5.

Chandio, A. A., Asikuzzaman, M. D., & Pickering, M. R. (2020). Cursive Character Recognition in Natural Scene Images Using a Multilevel Convolutional Neural Network Fusion. *IEEE*, 8, 109054-109070

Demilew, A.F., & Sekeroglu, B. (2019). Ancient Geez Script recognition using deep learning. *Springer Nature Journal.* https://doi.org/10.1007/s42452-019-1340-4

Fenwa, O.D, Omidiora, E.O and Fakolujo, O.A , Ajala, F. A., & Oke, A. O. (2012). A Modified Optical Backpropagation Neural Network Model in Online Handwritten Character Recognition System. *International Journal of Computer Application, 2(4),* 190-201

Goltsev, A., & Rachkovskij, D. (2005). Combination of the assembly neural network with a perceptron for recognition of handwritten digits arranged in numeral strings. *The Journal of the Pattern Recognition society, 38,* 315-322

Goswami, R., & Sharma, O. P. (2013). A Review on character recognition Techniques. *International Journal of Computer Applications, 83(7),* 19-23

Guo, Y., Liu, Y., Oerlemans, A., Lao, S., Wu, S., & Lew, S.M. (2015). Deep learning for visual understanding: A review. *Journal of Neurocomputing*, 1-22. Http://dx.doi.org/10.1016/j.neucom.2015.09.116

Jangid, M., & Srivastava, S. (2018*).* Handwritten Devanagari Character recognition using Layer- wise training of deep Convolutional Neural Networks and Adaptive Gradient Methods. *Journal of Imaging, 4(41),* 1-14.

Kadir, M. N., MohdHidayah, S., Mohammad, N., & Ibrahim, Z. (2019). Comparison of Convolutional neural network and bag of features for multi-class font digit recognition. *Indonesia Journal of Electrical Engineering & Computer Science, 15(3),* 1322-1328

Kala, S. L. (2022). Handwritten Character Recognition Using Neural Networks. *International Journal of Advanced Research in Computer and Communication Engineering, 11(4),* 168-171

Kaur, D., & Kaur, Y. (2014). Various image segmentation Techniques: A review. *International Journal of Computer Science and mobile computing, 3(5),* 809-814.

Khan, M. M., Uddin, M. S, Parvez, M. Z., & Nahar, L. (2021). A squeeze and excitation ResNext- based deep learning model for Bangla handwritten compound character recognition. *Journal of King Saud University-Computer and Information sciences.*

Kluzner, V. (2009). Word-Based Adaptive OCR for Historical Books. *10th International Conference on Document Analysis and Recognition,* 501-505

Kumar, G., & Bhatia, P.K. (2014). A detailed review of feature extraction in image processing systems. *Fourth international conference on advanced computing and communication,* 1- 12. IEEE

Kumar, P., Sharma, N. & Rana, A. (2012). Handwritten character recognition using different kernel based SVM classifier and MLP Neural Network (A comparison). *International Journal of Computer Application, 53(11*), 25-31.

Lukasik, E., Charytanowicz, M., Milosz, M., Tokovarov, M., Kaezorowska, M., Czerwinski, D. & Zientarski, T. (2021). Recognition of handwritten Latin Characters with diacritics using CNN, *Artificial and Computational Intelligence*, *69(1*), 1-12

Madakannu, A., & Selvaraj, A. (2019). DIGI-Net: A deep Convolutional Network for multi- format digit recognition. *Neural Computing and Applications.* https//doi.org/10.1007/s00521-019-04632-9

Medjahed, S.A (2015). A comparative study of feature extraction methods in image classification . *International journal of image, graphics and signal processing, 3*,16- 23

Mohan, M., & Jyothi, R. L. (2015). Handwritten character recognition : A comprehensive Review on Geometrical Analysis. *Journal of Computer Engineering*, *17(2),* 83-88

Mustafa, M., & Elbashir, M.K. (2020). A deep learning approach for handwritten Arabic names recognition. *International Journal of Advanced Computer Science and Applications, 11(1),* 678-682

Narang, S., Jindal, M.K., & Kumar, M. (2019). Devanagari Ancient Documents Recognition using Statistical feature extraction techniques. *Sadhana, 44(141*), 1-8

Narang, S.R, Kumar, M., & Jindal, M.K. (2021). DeepNet Devanagari: A deep learning model for Devanagari ancient character recognition. *Multimedia, Tools and Applications:*doi:10.1007/s11042-021-10775-6

Naseer, G.J, Basit, A., Ali., I. & Iqbal, A. (2020). Balochi Non-Cursive isolated character recognition using Deep Neural Network. *International Journal of Advanced Computer Science and Applications*, *11(4*), 717-722

Nasien, D., Haron, H. and Yuhaniz, S.S (2010). Support Vector Machine (SVM) for English handwritten character recognition. *Second International Conference on Computer Engineering and Applications*, 249-252

Nayak, J., Naik, B., & Behera, H.S. (2015). A comparative survey on Support Vector Machine in Data Mining tasks: Application & Challenges. *International Journal of Database Theory and Application, 8(1),* 169-186.

Odumuyiwa, V., & Osisiogu, U. (2019). A Systematic Review on Hidden Markov Models for Sentiment Analysis. *In 15th International Conference on Electronics Computer and Computation.*

Ojumah, S., Misra, S., & Adewumi, A. (2018). A Database for Handwritten Yoruba Characters. *in Communications in Computer and Information Science*. doi: 10.1007/978- 981- 10-8527-7_10

Oladele, M., Adepoju, T.M, Olatoke, O.A and Ojo, O.A. (2020). Offline Yoruba handwritten word recognition using geometric feature extraction and support vector machine classifier. *Malaysian Journal of Computing*, 5 (2), 504-514

Oladele, M., Omidiora, E.O ,Temilola, A., & Sobowale, A.A. (2017). An Offline Yoruba Handwritten Character Recognition System using Support Vector Machine. *International Conference of Sciences, Engineering & Environmental Technology, 2(13),* 95-103

Oyeniran, O., & Oyebode, E. (2021a). Transfer learning based offline yorùbá handwritten character recognition system. *Journal of Engineering Studies and Research*, 2(27), 89- 95.

Oyeniran, O.A. & Oyebode, E.O. (2021b). Yorùbánet: A deep convolutional neural network design for yorùbá alphabets recognition. *International Journal of Engineering Applied Sciences and Technology*, 5(11), 57-61

Pareek, J., Singhania, D., Kumari, R. R., & Purohit, S. P. (2020). Gujarati Handwritten Character Recognition from Text Image. *Procedia Computer Science,171(2020)*, 514-523

Pietrzykowski, M., & Salabun, W. (2014). Applications of Hidden Markov Model: State-of-the- art. *International Journal of Computer Technology & Application, 5(4)*, 1384-1391

Pithadia, N. J. & Nimavat, V. D (2015). A review on Feature extraction Techniques for optical character recognition. *International Journal of Innovative research in computer and communication Engineering*, 3(2), 1263-1268

Rani, N. (2017). Image processing techniques: A review. *Journal on today's ideas-tomorrow's Technologies, 5(1)*, 40-49

Rani, N.S, Chandan, N., Jain, A.S., & Kiran, H.R. (2018). Deformed character recognition using Convolutional Neural Networks. *International Journal of Engineering & Technology, 7(3),* 1599-1604

Saini, S., & Arora, K. (2014). A study Analysis on the different image segmentation Techniques. *International Journal of information & Computation Technology*, *4(14*), 1445-1452.

Sakshi Indolia, S., Goswami, A. K, Mishra, S. P., & Pooja Asopa (2018). Conceptual Understanding of Convolutional Neural Network- A Deep Learning Approach In *International Conference on Computational Intelligence and Data Science, 132*, 679–688

Sarker, H.I. (2021). Machine learning: Algorithms, real-world applications and research directions. *Computer Science*, 2:160

Senthilkumaran, N., & Rajesh, R. (2009). Edge Detection Techniques for Image Segmentation-A Survey of Soft Computing Approaches. *International Journal of Recent Trends in Engineering, 1(2),* 250-254.

Shivhare, P., & Gupta, V. (2015). Review of image segmentation techniques including pre and post processing operations. *International Journal of Engineering and Advanced Technology, 4(3),* 153-157

Sonara, H., & Pandi, S.G. (2021). Handwritten Character Recognition Using Convolutional Neural Network. *In 3rd International Conference on Communication and Information Processing, 1-9*

Sujata, S., & Verma, V. (2019). Japanese Historical character recognition using Deep Convolutional Neural Network with dropblock regularization. *International Journal of Recent Technology and Engineering, 8(2),* 3510-3515

Sujatha, P., & Bhaskari, L.D. (2019). Telugu and Hindi Script recognition using deep learning techniques. *International Journal of Innovative Technology and Exploring Engineering, 8(11),* 1758-1764.

Sumithra, K., Buvana, S., & Somasundaram, R. (2015). A Survey on various types of image processing techniques. *International journal of Engineering research and technology*, *4(3),* 399-403

Zhang, Y. J. (2006). An overview of image and video segmentation in the last 40 years. *In Advances in Image and Video Segmentation,* 1-16.