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A Comprehensive Literature Review on Air-written Online Handwritten Recognition

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Abstract: The COVID-19 pandemic has shifted ordinary life into a digital platform. Individuals rapidly use digital or online media to avoid the impact of touch-based platforms. In this case, touchless technology is primarily used in operation theatres, online education systems, ticket counters, etc. However, the online numerals or characters written in the air are challenging to recognize efficiently due to the writing styles of every individual. Therefore, the present research focuses on recent work on online air-written handwritten recognition. Almost eighty-plus standard articles on handwriting recognition from various journal/conference databases are considered for the current review. In addition, the generalized methodology of handwriting recognition is also provided for new research. It is observed that some online handwritten databases for some languages are freely available for research purposes. However, the online real-time air-written numeral dataset is private for Devanagari and English. Therefore, designing and developing a standard dataset for character or numeral recognition written in the air is suggested. The earlier studies achieved satisfactory results on air-writing multilingual numerals collected via or without sensors using advanced machine learning and deep learning methods. The convolutional neural network (CNN) has provided the best accuracy for several languages, excluding Devanagari.

Keywords: Air-writing data, online handwriting recognition, air written recognition, convolutional neural network, Devanagari/English numeral dataset

1. Introduction

Due to the COVID-19 pandemic, the world has quickly shifted towards the online/digital world [1], [2]. In the numerical age, intelligent devices require a human-computer interface to understand handwritten data, leading to a paperless society accurately. Handwritten documents can become damaged over time. Thus, appropriate indexing and storage systems are crucial [3]. Numerous exciting features of numerical reports include organizing and ordering a vast amount of data for further processing, such as record recovery. In this case, the researchers suggest focusing on character and numeric recognition. Online and offline handwriting detection are the two groups used in the past. Due to the extensive use of touchless technology, handwriting is subclassified into offline, online and air-written [3]. When a printed or handwritten document is scanned to produce a number form, the writing on the offline paper can be recognized. However, we cannot search for a character or numeral in this numerical document because it is a picture. A text from multiple copies must be transformed to ASCII or Unicode format to search for [4].

One document in handwritten character/numeral recognition may contain many languages. Nevertheless, every person has unique handwriting. In handwriting recognition, a text block is first distributed into lines, then those lines are distributed into words, and finally, comments are distributed into isolated characters/numerals [3]. For many scripts, a different writing method is used [4]. The hand is a writing that some languages use to indicate characters and numbers. For instance, the Brahmic script uses the Abugida writing system, which is used for most Indic languages [4]. Numerous character recognition algorithms have been proposed to transition to a paperless society [5], [6], [7], [8]. The character recognition survey studies come in several forms, but most are based on offline character recognition. Some academic works have concentrated on online handwritten character recognition. However, either Non-Indic Script or Indic Script serves as the basis for both of these works, i.e., online and offline. With the different Optical Character Recognition (OCR) systems and OCR methodologies, an identical set of letters, pictures, and symbols must be used to assess and benchmark the studies. The study [9] contains a thorough systematic literature review (SLR) of OCR

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approaches.

A study [10] thoroughly analyzed handwritten Indic script identification using pre-processing, feature extraction, and classification strategies [10]. The study [11] focused on the outcomes obtained using various hand-written, in-print, and mixed-text processing approaches and procedures [11]. The authors [12] created a compact online recognizer for a significant handwritten Japanese character set using the vector quantization approach on distributed characters, applying a Markov random field and well-framed dictionary illustration. The study [3] surveyed the numerous script recognition approaches based on frame and visual impression. The study [13] analysed several well-known scripts, including Roman, Arabic, Chinese, and Indian. Some Indian languages, such as Tamil, Devanagari, Oriya, Bangla, and Gurmukhi handwritten Indian scripts have been reviewed by authors [14]. A study on the Indic scripts was given in [15]. Authors [6] describe the core of the handwritten language, the procedures for obtaining digital information, and the essential ideas of language detection methods for both online and offline. For documents with many scripts, script identification is a critical stage in the OCR process. A predefined accumulation of symbols and pictorial features in syntax is known as scripting. Each script contains unique components that set it apart from others. Script recognition is essential for automatically understanding papers that are written in hand. Authors categorized and examined numerous script identification techniques for document photographs in [7], and they compared the various schemes based on their advantages and shortcomings.

The earlier studies have not focused on air-written online handwritten numeral recognitions. Therefore, this article focuses on a systematic literature review on recognizing online handwritten numerals in several scripts. This literature review examines many methods and thoroughly examines online number handwriting recognition. The Online Handwritten Recognition (OHR) system correctly identifies an input character's data. The social justice system has changed how online handwriting analysis is done. In this case, we focus on research on OHR published in seventy-plus reputed journals and conferences. We've also provided a selection of reputable OHR tools. The paper's organization is divided into ten parts. This section briefs about the scenario of online handwriting recognition. Sections two and three give motivation, objectives, challenges, and research review methodology. Section four highlights the use of handwriting recognition with online and offline approaches. This section also covers the devices used for capturing online handwriting data and applications of online handwriting recognition. Sections five and six focus on sensor-less and with sensors air-written multilingual recognition. Section seven provides the online character identification databases that are currently accessible. Methodologies used for air written numeral recognition and limitations of existing systems have been discussed in sections eight and nine, respectively. The final part wraps up the current literature review and discusses upcoming studies.

2. Motivation, Objectives, and Challenges

Over the past few decades, researchers have become increasingly interested in handwriting recognition studies. Nowadays, there is a significant advancement in online writing recognition. However, there is always a remarkable performance difference between humans and machines. Handwritten data could be successfully reinterpreted and digitized by cutting-edge technology like smartphones and digital computers. Therefore, online handwriting recognition is helpful for various purposes. The challenge, however, is reading characters written in varied handwriting styles, sizes, and shapes. Finding writing hand poses to start air-writing is difficult. Some writers may employ several writing techniques, which makes text recognition challenging for a machine. Precise fingertip detection and tracking in inadequate real-time light, cluttered background, and blurred finger motion are complex [16]. Numeral recognition in a handwritten system is complex compared to printed numeral recognition due to the variation in writing styles, strokes etc. Accurate detection continues to be challenging due to the tiny facet of the finger [17]. Online handwriting detection is difficult because many databases are used for various methods, feature extraction techniques, and accuracy levels.

Table 1: Difference between the present survey and earlier studies

Reference	Details about the study
Ghosh et al. [3]	1. Several writing strategies were described in detail. 2. Printed materials took priority. 3. There are just five to six published studies on online handwriting recognition.
Singh et al. [18]	1. Only eight Indian and six foreign scripts received priority. 2. There has yet to be any known research on the multilingual script recognition.
Menon et al. [19]	1. Strictly focused on studies conducted between 2000 and 2019 only. 2. Various OCR classification methods and online/offline datasets are reported.
Proposed study	1. Coverage ranges from the fundamental to the commercial system. 2. Numeral and numeral string recognition is covered regardless of the language. 3. This review also mentioned multilingual numeral recognition. 4. The OHR research trends at various levels are discussed, and it is then recommended where the research may go.

Thus, the paper summarizes the study and reviews

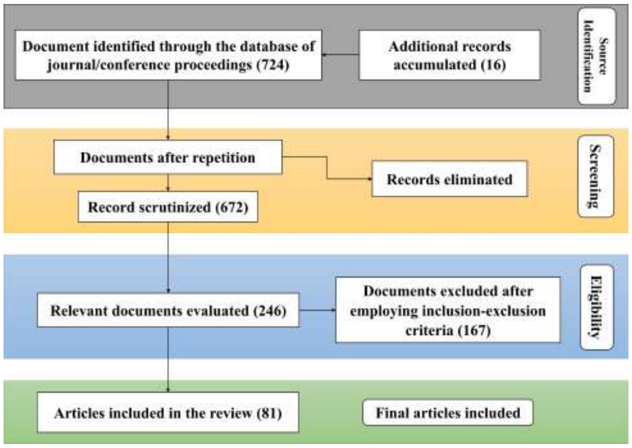

Figure 1. Flow chart as the essential elements of a systematic review.

current developments in online symbols, words, and unrestricted text distinction. Table 1 lists the primary variations between recent and previous survey iterations.

3. Review Methodology

In the present review, we divided several methods for computerized handwriting analysis into three levels: recognition based on offline handwriting, online handwriting, and recognition based on air written. Published articles are considered from reputed journals and conferences. In handwriting recognition, numerous existing approaches were developed by various academics. These handwriting recognition technologies must be investigated to consider the broad context. This data compiles journals, research articles, books, conference/symposium proceedings, and other sources. For the current study, reliable sources were used, including the ACM Digital Library (www.acm.org/dl), Springer (www.springerlink.com), IEEE Xplore (https://ieeexplore.ieee.org), Elsevier (https://www.elsevier.com/en-in), ResearchGate publications, conference/symposium proceedings, and pertinent websites. The four steps of identification, screening, eligibility, and inclusion are shown in Figure 1 flow chart as the essential elements of a systematic review.

4. Research On Handwriting Analysis

Handwriting analysis includes the identification and verification of writers. Studies on handwriting analysis are scarce, and even fewer studies worked on online handwriting recognition. When comparing writing styles, handwriting individuality provides a quantifiable measure of the distinctive characteristics of the author that can be used to determine who wrote a given document and to weigh the significance of any similarities and variances. Handwriting is also a biometric trait to verify and recognize the person. Additionally, a biometric feature that can be verified automatically feeds the highest level of protection. As a result, biometric characteristics like handwriting and handwritten signatures assure security in many contexts, especially in financial and ethical contexts. The method of identifying the writers of the provided handwriting samples is known as an identification scheme [20]. In contrast, determining the original writer from the provided data samples is known as verification [21].

Some studies have worked on handwriting signatures and character recognition. For instance, the authors [22] suggested a CNN model to create offline writing research using handwritten photographs. A Siamese architecture is used to confirm the writer and a recurrent neural network (RNN) generates English words to explain the reasons for similarity/discrepancy between writers [21]. In addition, some studies [23] have focused on identifying offline signatures using offline signatures.

The study extracted important individual traits from a specific collection of Kanji characters via online Kanji handwriting [24]. In study [25], authors introduced an end-to-end writer label technique for 144 works using RNN, taking into account the database that includes 133 authors in English and 186 writers in Chinese. Indian and non-Indian languages, including Gurumukhi, Oriya, Bengali, Telugu, Gujarati, Chinese, Kannada, Malayalam, Arabic, Tamil, French, Persian, and Roman, have all been used to identify the source [26]. A thorough review of the verification of handwritten Western and Indic signatures was done in the study. The research used machine learning to conduct a script perspective poll on writing recognition [27]. Several studies on a variety of topics, including gender identity, hand preference, and early neurological disease diagnosis, have been published in [28], [29], [30], [31] based on handwriting analysis.

A. *Offline handwriting recognition*

Offline and online handwriting recognition are the two subfields of the handwriting recognition discipline. To perform offline handwriting recognition, the writer notes on paper, scans or digitalizes it, and stores it as a picture. Suppose someone scans and transmits an image to someone else, and the receiver wishes to make changes. In that case, texture recognition can only be accomplished because the picture does not permit text searches or alterations. Research on offline handwriting recognition has been successful in fields including reading postal addresses, checking bank checks, processing forms, etc. [32]. The offline handwriting character can be found using any of the following processes: picture capture, preprocessing, segmentation, feature extraction, selection, and categorization [33]. For OCR, it is necessary to have a preprocessed scanned document and a good resolution, but owing to scanning, this type of image has poor resolution [34]. Character recognition is hampered if a record has numerous scripts. Numerous scholars have conducted in-depth studies on offline handwritten character recognition based on Indic [35], [36], [37], [38], [39] and non-Indic [35], [37], [40], [41], [42] scripts.

Table 2: Recognition accuracy achieved for various offline handwriting recognition systems.

Authors	Language / Script	Level	Recognition Accuracy	Advantages	Limitations
Pal and Chaudhuri [35]	Chinese, Arabic, Devnagari, Roman, and Bangla	Text	97.33%	Five languages with good Accuracy	Used the printed documents
Gopakumar et al. [36]	Hindi, English, Kannada, Telugu, Tamil, Malayalam, and Tamil	Text	100%	Seven Indian languages were used and achieved 100% recognition accuracy	The system is tested and validated on a limited dataset.
Prasanthkumar and Dileesh [37]	Tamil, Hindi, Malayalam, and English	Word	81.69%	Four Indian languages are considered	Recognition accuracy is very less.
Singhal et al. [38]	Latin, Bengali, Telugu, and Devnagari	Page level	91.6%	Four languages are considered	Recognition accuracy is very less
Jawahar et al. [39], [43]	Telugu and Devnagari	Word	92.3% to 99.86%	Two Indian languages are considered	Recognition accuracy is very significant for Telugu
Benjelil et al. [40]	Latin and Arabic	Word	97.5%	Good recognition accuracy	Worked only for Latin and Arabic Language
Zhou et al. [41]	English, Hindi, Thai, Arabic, Chinese, and Korean	Text	Arabia: 97.33% Chinese: 98.00% English: 96.77% Japanese: 98.00% Thailand: 98.67% Korean: 96.77%	Six languages are considered	Recognition accuracy is less and varies for different languages
Moalla et al. [42]	Latin and Arabic	Word	100%	Two Indian languages are considered	This is word-level recognition
Moussa et al. [43]	Latin and Arabic	Text	96.64% by using KNN and 98.72% by using RBF	Good recognition accuracy	Worked only for Latin and Arabic languages are considered
Elgammal and Ismail [44]	Latin and Arabic	Line	96.8%	Two Indian languages are considered	The work is line-based recognition accuracy

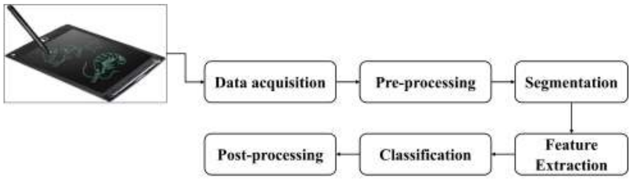

Figure 2. A generalized block diagram of the handwriting recognition approach.

As shown in Table 2, the foundation of every study is the identification of writing in both handwritten and machine-printed texts. However, the earlier studies only offered an algorithm for the recognition of printed documents in [35], [38], [39], [42], [44]. Some studies have described their work on printed and handwritten recognition [37], [40], [43], [45]. Other substantial works based on offline handwriting recognition are suggested in [46], [47], [48], [49], [50]. Table 2 displays the accuracy obtained by several offline handwriting recognition algorithms.

B. *Online handwriting recognition (OHR)*

The OHR involves the automated conversion of text entered into a particular digitizer, where a detector takes information about moving the pen up and down in addition to the movements of the pen tip. The users can use a stylus or electronic pen to write on electronic devices, much like a conventional pen and paper-based system. The OHR uses contextual data, such as position, direction, velocity, etc., to create a dynamic or real-time computer representation of the pen action. Online handwriting data makes it simple to search for and retrieve information.

A regular handwriting detection system is composed of six steps: image/data gathering, preprocessing, segmentation, feature extraction, classification, and lastly, post-processing (Figure 2). Data acquisition refers to creating relevant datasets using information from several unrelated sources. Similar points elimination, smoothing, size normalization, and resampling are all included in the preprocessing stage. The segmentation process divides digital data into different portions to make the display more straightforward, understandable, and easier to analyze. Each letter is interpreted as a trait vector during the feature extraction, improving detection rates. Features are distinctive traits that help us recognize a letter or word. The classification phase, which leverages the features inferred for identification from the prior stage by refining the choice made in the preceding step, is the crucial decision-making stage: The third stage, post-processing, encourages recognition. Figure 2 illustrates the handwriting recognition method's generalized diagram.

In real-time data collection, quality information such as pen strength, the direction of pen movement, and other factors are used. However, nowadays, modern cell phones and laptops come with touch-sensitive screens, which enable users to annotate the screen using a finger or electronic pen instead of the keypad [3]. For instance, the word sample is recorded and preprocessed utilizing an internet tool shown in Figure 3.

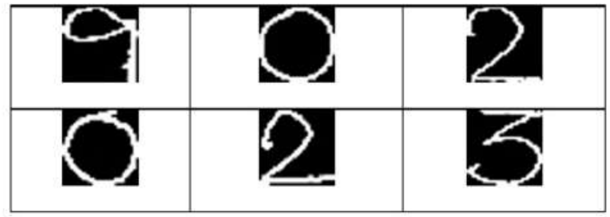

Figure 3. A model data captured by a generic webcam and preprocessed images of Devanagari and English numerals.

1) *Online handwriting capturing devices*

Most individuals still feel comfortable using pen and paper, even if taking digital notes on computers and phones is simple. However, the issue is that we need help to easily browse and preserve handwritten notes the same way we can with digital ones since dynamic information can reveal essential details like the number of strokes and their sequencing. Thus, it is crucial to recognize online handwriting. Specific intelligent devices, however, can examine our drawings as we type. These instruments can retain all the data required for the online identification of letters, including coordinate weights, pen-up and pen-down samples, slope, shape, moderate letter size, stress on the document, and spacing between the strokes and characters. The "Take Note" is a storage-capable gadget that digitally captures handwriting and ink drawings made on regular paper without operating a computer or other special software.

Several Wacom products, including the "Wacom One and Intuos" and "Bamboo slate", can capture handwriting from the internet. With the "CrossPad", we can write and send electronic notes on a portable notepad. This digital pen uses radio transmission to store information on the tablet. With "DigiMemo's" online writing feature, handwriting on paper and the digital page may be automatically synchronized. Over the digitizing pad, the sheet is positioned on the device, and as the pen writes, its location is registered as X-Y coordinates and saved in the device's onboard memory [48]. Another digital writing pad, "iScribe", requires a special pen and a regular refill and can handle A4-sized paper that can be used to record online handwriting. With its annotation features, we can edit PDF files also. Anyone ca48 [48] uses this gadget to write while retrieving info digitally.

In addition to paper, the gadget utilizes USB connectivity features on a notebook. "Supernote," which enables users to capture and retain notes in the same digital format, is another gadget that blends contemporary technology and the conventional notebook. The "WDCT" is a tablet-based application with a visual user interface for gathering examples of handwriting data from further writers. The result of

Figure 4. Handwriting capture online tools (a) Tablet PC, (b) PDA, (c) Digital Tablet, (d) Optic Pen.

the device is a collection of directory-structured UNIPEN files that include writer shapes, explanations of the gathering procedure, and digital ink. HP Labs India developed the "Lipi Toolkit (LipiTk)," an online handwriting detection open-source toolkit. Open standards like UNIPEN are used by LipiTk 1.0 to represent digital ink [51] and its annotation [52]. Figure 4 lists the top online handwritten detection tools (CrossPad, Take Note, iScribe, Supernote, PDA, DigiMemo, Bamboo Slate).

C. Online script identification

Script identification becomes highly important in situations involving numerous languages because every method for reading handwritten text is language-specific [49]. A dedicated mechanism for recognizing scripts is necessary to automate the distinction procedure [4], [11]. Characters can be written with a pen; most hands are straight or curved, founded on strokes. The script-identifying method is one of the most crucial elements of multi-script text analysis. Online handwriting analysis examines the placement of the lines.

A three-script identification system for Arabic, Tamil, and Roman was suggested, derived from an information recovery technique. Using the KNN classifier, the line segments from the training set were grouped. The chi-square distance classifier forecasted an intermediate script recognition rate of 93.3% [50].

The authors [18] suggested the Telugu, Devnagari, Bangla, and Roman handwritten page-level character identification. According to the study, the Multi-Layer Perceptron (MLP) classifier has an accuracy rate of 91.48%. Similar to this, the authors used eleven bi-script variations, including Roman-Gurumukhi, Roman Telugu, Roman-Urdu, Roman-Kannada, Roman, Bangladesh, Roman-Devanagari, Roman-Tamil, Roman-Oriya, Roman-Gujarati, and Roman-Malayalam. They also combined Roman-Devanagari with one regional script to create tri-script combinations, achieving the highest accuracy rates for bi-script and tri-script, at 98% and 96%, respectively [53].

D. Applications of online handwriting recognition (Air writing Recognition)

The OHR has a significant role in the global transition to a paperless workplace. Online handwriting programs are designed to assist people in writing in their preferred manner while also digitizing their handwriting for future use. In addition, the OHR has the crucial benefit of requiring less storage space than physical copies. Searching for and getting the necessary information from a digital record is more straightforward than a hard copy document. The OHR reduces the price of transportation, manual duplication, and the likelihood of document loss. A digital record is much easier to maintain and update than a paper document regarding routine updating. The only method to protect the digital copy from a catastrophe is to keep it. In the banking industry, OHR can assist with customer signature verification. Online handwriting is also used for writer verification. This parcel delivery method makes it easier for the recipient to know about and preserve a delivery record. In medicine, OHR is used to identify the gender of unidentified authors, assess neurological diseases, and administer psychometric exams to the writer [28]. Therefore, to get the best results from the OHR, we must conduct a comprehensive study to maintain our documents secure, accessible, and affordable.

The use of OHR can be summed up as follows:

• OHR offers users a setting similar to that of a pen-and-paper method., decreasing the time spent searching because finding anything in a hard-copy document is difficult.

• It is simple, inexpensive, and requires little space to store and share digital documents.

• Digital papers make editing more accessible, and OHR allows us to save our work for future use.

• Capturing the online handwriting allows for writer identification and verification.

• OHR is also applicable in the field of medicine.

5. Air-Writing Multilingual Numeral Recognition with Sensors

OCR systems have a subfield called "air-writing", in which hand or finger motions are used to write letters or numerals in space. The text can be written into the air with sensors and character motions, such as writing on a virtual whiteboard. We can track the movement of the finger or handheld device. Several studies have reported using sensors to recognize air-written multilingual numerals. For instance, the study [16] demonstrated the ability of a wearable device to identify hand actions for air writing. The gloves were designed to be worn on the hand and equipped with accelerometers, motion sensors, angular rate sensors, and smartphones.

Additionally, Bluetooth technology is used to record and transmit signals. An accelerometer and gyroscope capture movement signals in a wearable hand motion-tracking device. However, due to inertial sensor drift, translating the acceleration data into crucial characteristics for stroke recognition might need to be more accurate. The sensors were linked to a glove to read the hand motions, and a computer system was used to gather the necessary signals, which convert them to text, resulting in an e-mail, message (text), or another Android app [54].

The study [55] proposed a method for recognizing various handwriting styles on images using the varied forms of letters or numbers using the strokes model. The ligature model attempted virtual 3D characters from 2D structures and applied the Bayesian model to detect actual on-air writing. The method writes the English alphabet in an unconstrained environment, resulting in a training model employing natural on-air-writing motions. Shape and motion features were used in the time series. However, an algorithm has been proposed for gesture recognition using an IR-UW Bradarsensor [56]. The proposed method uses an infrared camera in an innovative device environment to track the tip of a finger and space touch hand gestures. This method estimates the end of a finger using a curvature-based ellipse-fitting algorithm and is verified using an ellipse-fitting rectangular area of some fixed value [57]. The intelligent gloves were created using a sign language-to-voice conversion mechanism for hand motion recognition. The authors [58] developed a more adaptable and precise system for measuring hand motions using flex sensors and an inertial measurement unit. An indication is shaped by the sensors appreciating the hand sign. The controller coordinates the motion with pre-stored inputs.

On the other hand, authors [59] have focused on fine-tuning the sensor and using this sensor afterwards to create an editable document from handwriting. Transferring ideas from scrawled notes to a usable digital copy requires time. The answer to this issue is a pen that utilizes its action to move penmanship into an editable Word document. It recommends using the dynamics of the writing process to handle the problem. To capture the movements of the stylus, the gadget has a gyroscope and accelerometer devices. To reconstruct the phrase, various mistake corrections are used to convert the raw motion sensor data into processed, usable data.

In the study [60], recent vision sensors that can record 3D finger locations and motions have been explored by writers. It offers a ground-breaking method of commanding and interacting with computers by simply moving your palms outdoors. We can identify users' intended input information by tracking the moving fingers. Using handwriting recognition as an example, it illustrates the human input approach. A quick algorithm with dynamic time warping is proposed with a time-series input to identify characters on the internet. However, segmentation strategies were employed to identify the data points. It is challenging to pinpoint the segments' start and end, making this work difficult. As a result, data-driven techniques and unsupervised learning are usually used. For this task, the statistical techniques to recognize characters use HMMs or a combination of HMMs and neural networks. The alignment method of Hilbert Warping has been proposed for handwriting recognition [56].

A LED pen to track characters in the air is one of the additional scenarios that have been put out. The technique makes it possible to analyze 3D data and guarantees that the start and stop of input are distinct. The handwriting issue can be approached similarly to speech recognition, with the input points being thought of as signals. Though, the identification accuracy is a challenge with these methods.

Table 3. Summary of air-writing multilingual numeral recognition with sensors

Dataset	Sensors/Methods	Accuracy	Reference
—	flex sensors and Inertial Measurement Unit (IMU)	—	[59]
—	IR-UWB radar sensors	96%.	[60]
self-generated	HMMs	99 %	[61]
self-generated	Bayesian	recognition rate: 900 chars: 78.6% 2,350 chars: 64.0%	[62]
—	accelerometer sensor	93.39%	[63]
—	vision sensors	—	[64]
—	depth sensor	1.9% for letter-based identification and 0.8% for word-based recognition, respectively, is the word mistake rate.	[65]

Air writing provides a tactile experience, unlike traditional penmanship on paper or another medium, which does not. The report appears organically drawn in the air in uni-stroke without any pen-up and pen-down details. A continual stream of sensor data like movement motions follows air-writing. The user imagines and writes in a writing box without receiving haptic feedback. Additionally, air writing does not need to be read aloud. Motion characters—separate alphanumeric letters created with a single, continuous stroke, are used in air-writing, as are motion words. For online handwriting recognition, HMMs are well known. In ligature, which connects letters without using explicit pin-up moves, models are provided to handle online cursive handwriting detection. Motion-based handwriting is comparable to motion gestures or signs in that sense. Many sign-language identification systems use HMMs with various sensing skills, including data gloves and vision-based methods. With inertial sensors linked to a glove, air-writing recognition was made possible. A depth sensor tracks finger writing in the air. Different motion detection and tracking methods subject the user to various behavioural pressures. As an illustration, many users view wearing data gloves as an unwelcome weight that could alter their movement patterns [64]. The air-writing multilingual numeral recognition has been done using sensors (Table 3). Table 3 illustrates the accuracy and use of air-writing multilingual numeral recognition using sensors.

However, the studies reported in [59], [60], [64], [61], [62], [63], [65] worked on air-writing multilingual numeral recognition. These studies have used various sensors to capture air-writing data used as input for further processing. However, these studies' recognition results vary due to dissimilar sensors and methodologies.

6. Air-Writing Multilingual Numeral Recognition Without Sensors

You can air-write without instruments by using your hand or finger to make letters or numbers in a blank area before a camera. However, there are few studies on air-writing without sensors for international number identification (Table 4). For instance, the study [66] presented a sliding window-based technique for removing noise and segmenting digits from a tiny portion of the spatiotemporal input from the air-writing activity.

Table 4. Summary of air-writing multilingual numeral recognition without sensors

Dataset	Classification Method	Accuracy	Reference
MNIST and Pendigits English numerals dataset (ISI-Air Dataset)	RNN	single digit:98.45% multiple digits: 82.89%	[67]
0–9 numbers and English alphabets a to z	R-CNN	96.11%	[68]
MNIST, Pen digits, ISI-Air English single and multi-digit Numerals	RNN-LSTM	85.27% for multi-digit and 98.75% for single-digit	[69]

When handling temporal data, the RNN demonstrate a substantial level of accuracy. A combination of MNIST and pen digit datasets and the trials' unique air-written English numeral dataset were used to study English numerals (ISI-Air Dataset). The algorithm produced 98.45% and 82.89% accuracy values for single-digit and multiple-digit English numbers, respectively. The authors [66] presented a novel technique for identifying writing hand locations using the faster region-based CNN (R-CNN) architecture for accurate hand detection and segmentation. The number of raised digits was also tallied based on the hand's geometrical features. They also suggest a reliable fingertip recognition and tracking strategy that uses a brand-new signature function termed distance-weighted curvature entropy. They attained 96.11% accuracy with the proposed air-writing approach. Air-writing character identification accuracy was 96.10% when using the EMNIST dataset's 0–9 numbers and small English alphabets.

Similarly, the study [63] has proposed a method for identifying multi-digit numbers drawn with a video camera that records airwriting. Using the MNIST, ISI, and pen digits datasets for their tests, they produced single- and multi-digit English numbers with 98.75 and 85.27% precision. The studies on air-writing multilingual numeral recognition without sensors used RNN and CNN methods with satisfactory performance (Table 4).

Most of the research work reported (Table 5) is on its own developed dataset on characters and numerals in different scripts/languages since no benchmark dataset is available. Specific air-written character recognition systems without sensors have reported a maximum recognition accuracy of 96%. Also, numeral recognition is addressed with a maximum 98.45% accuracy.

7. Publicly Available Datasets

Enormous amounts of data are required to create real-time air-written handwriting numeral recognition systems with high recognition accuracy for training and testing. The main goal in the advancement of handwriting recognition research is compilation. The most famous attempts at real-time air-written handwriting numeral recognition databases are discussed in the present section.

7.1 IAHCC-UCAS2016: The dataset contains 3811 Chinese characters (i.e., 3755 characters from the standard level-1 set of GB2312-80 + other 56 frequently used characters), each type has 115 patterns in the IAHCC-UCAS2016 dataset. We organized more than 500 volunteers to collect data [63].

7.2 IAHEW-UCAS2016: The constructed collection comprises 150,480 recordings spanning 2280 English words, each with 66 distinct examples. Three hundred twenty-four additional individuals have provided data to the project [63].

7.3 IAHCT-UCAS2018: 15,671 text lines with 260,224 characters constitute the first in-air handwriting Chinese text collection. The entire dataset is divided into a training set and a test set, with the data from 277 authors (11,807 lines and 196,129 characters across 3564 classes) being used for training and the data from the remaining 92 writers (3864 lines and 64,095 characters across 2397 classes) being used for testing [63].

7.4 The collection includes fingertip trajectories from five subjects' air-writing videos. The courses, which included ten examples for each character, were recorded for 36 characters, including English alphabet letters (from a to z) and integers (0 to 9). The air-writing films, which contain backdrops with various levels of complexity and luminosity, are captured with a standard webcam. One thousand eight hundred air-writing character trajectories have been recorded (10 samples of each of 36 characters from 5 people) [16].

7.5 To immediately implement the suggested framework, a standard air-writing dataset is still not readily accessible. Therefore, a library of air-written numbers is gathered to aid future trials. The data are recorded using a standard video camera and a set, uniform-color marking. An image of the marker tip's location is produced following marker segmentation, marker tip identification, trajectory approximation, and marker tip segmentation. A numerical identifier is then added to the dataset for each occurrence of the produced picture. Three distinct databases were produced for English, Bengali, and Devanagari numerals. Ten thousand air-written digits from 20 distinct individuals, each of whom penned one 417 characters 50 times, were gathered for each dataset [54].

7.6 Since there isn't public information that can be used for this, the authors [54] make two different datasets. A one-digit dataset has 20 symbols; the digits 0 to 9 are written in clockwise and anticlockwise directions. The other dataset contains directional characters with 16 signs [54].

7.7 There are 30,000 paths in the RealSense trajectory character (RTC) dataset1. Four thousand are for evaluating the model's precision, and 26,000 are for training and validation [54].

Table 6 highlights the air-writing multilingual numeral datasets collected without using any sensors.

8. Methodologies Used for Air Written Numeral Recognition

Several methods and approaches have been used in earlier research to tackle the problem of air-written numeral recognition. Researchers mostly used machine and deep learning-based methods in recognizing the numerals written in the air. For instance, machine learning with handcrafted features and deep learning with end-to-end learning were frequently used in earlier research [70].

A. Machine Learning-based approach

In machine learning with the process of a handcrafted feature, the numeral recognition system is divided into feature extraction and classification. In this case, the handcrafted-based features can be extracted from the raw input data (e.g., accelerometers or motion sensors capturing the gestures) and used to represent the gesture's characteristics [71]. Some commonly used handcrafted features are:

1) Histogram of Oriented Gradients (HOG)

This represents the distribution of gradient orientations in the gesture image.

2) Hu Moments

Capture shape information of the gesture using image moments.

3) Zernike Moments

Represent shape information as a series of orthogonal moments.

4) Discrete Fourier Transform (DFT)

Converts the temporal information of the gesture into frequency domain representation.

In classification tasks, some machine learning algorithms like SVM, k-Nearest Neighbors (k-NN), or Random Forests have been majorly used for classification [72]. However, the machine learning approach with handcrafted features presents some advantages and disadvantages. Some critical advantages and disadvantages are:

Advantages of Traditional ML with handcrafted features:

- Interpretable: Handcrafted features can be easily understood and interpreted by humans.

- Require less data: This approach might work well with smaller datasets than deep learning.

- Require less computational resources: Traditional ML algorithms are usually less computationally demanding than deep learning models [27], [71], [72].

Disadvantages of Traditional ML with Handcrafted Features:

- Limited expressiveness: Handcrafted features might not capture all the complex patterns and variations in the air writing gestures.

- Feature engineering: Designing effective, handcrafted features can be time-consuming and requires domain expertise.

- Suboptimal performance: The model's performance might be limited by the quality and richness of the handcrafted features [27], [71], [72].

Table 5. Summary of air-writing character recognition without sensors

Datasets	Classification Method	Accuracies	Reference	Advantages	Limitations
English Character- 1800 video	CNN	96.11%	[16]	Good Recognition Accuracy	Only one language
English numeral dataset- 13600 images	CNN	98%	[54], [57]	Good recognition accuracy	Only on English numeral dataset.
English Numeral dataset – one digit & multiple digits	CNN	98.45% and 82.89% for single and multiple-digit English numerals, respectively.	[55], [57]	Good recognition accuracy.	Only in the English language
English Character Dataset-26 image sequence	HW+EMD	90%	[56]	Good Methodology	Less recognition accuracy
Chinese Character – 3755 characters	CNN	92.81% for IAHCCR and 97.43% for HCCR	[63], [66]	Good Recognition accuracy	Experimentation on a small dataset
English, Bengali, Devanagari Numeral-10000 each	CNN	97.7%, 95.4% and 93.7% For English, Bengali and Devanagari numerals, respectively	[73]	Three Indian languages	Recognition accuracy is less

Table 6. Summary of air-writing multilingual numeral recognition datasets developed without sensors

Reference	Language / Script	Number of writers	Remark
[16]	English alphabet and numbers	5	1800 different air-writing character trajectories
[54]	English Numeral and Character	14	The digit dataset's training and test set sizes are 12,000 and 1,600, respectively. There are 9,600 and 1,280 in the directional symbol dataset, respectively. They have 30,000 trajectories in our RealSense trajectory character (RTC) dataset1.
[57]	English,Bengali, Devanagari	20	10000 air-written numerals
[63]	Chinese, English	500+	3811 Chinese character classes. 150,480 recordings covering 2280 English words. 15,671 text lines of 260,224 characters

B. Deep learning-based approach

Deep learning-based models have recently been primarily used in air-writing numeral recognition with the highest accuracy to recover the limitations in machine learning-based systems. In addition, deep learning offers an end-to-end learning approach, where the model learns to directly map raw input data (e.g., raw sensor readings or image sequences) to the desired output (numeral labels). In the context of air writing numeral recognition, researchers mostly used either CNN or RNN models to process the raw gesture data.

1) CNN:

This method is effective for processing image-based gestures. CNNs can automatically learn hierarchical features from the input images and capture spatial patterns. We can use 2D CNNs for static gesture images or 3D CNNs for temporal information in sequential gesture data [74].

2) RNN:

This method is suitable for processing sequential gesture data. RNNs can capture temporal dependencies and patterns in the air writing gestures. Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) cells are often used to handle long-range dependencies [75].

However, the deep learning-based models require some essential parameters to deal with it. The optimal values for hyperparameters in the air writing numeral recognition tasks can vary depending on the specific dataset, model architecture, and computing resources available. Though, some common approaches can be used as a baseline. However, they may need to fine-tune these values based on experimentation and validation [54], [55], [57], [63], [73], [54], [57], [54], [70].

1. Number of neurons: For CNNs, a moderate number of neurons in the hidden layers, such as 64, 128, or 256, can be used. For RNNs, similar values for the number of hidden units in each layer are required.

2. Activation function: ReLU (Rectified Linear Unit) for hidden layers and SoftMax for the output layer can be used when dealing with multi-class classification tasks like numeral recognition.

3. Optimizer: 'Adam' is suitable for most deep learning tasks, including airwriting numeral recognition

4. Learning rate: The' Adam' optimizer's standard initial learning rate can be 0.001 or 0.0001. Most researchers use learning rate scheduling to decrease the learning rate during training (e.g., using a learning rate decay).

5. Batch size: It can start with 32 or 64 batch sizes.

6. Epochs: Around 50 epochs can be sufficient to prevent overfitting [76].

Advantages of deep learning with End-to-End learning:

• Automated feature learning: Deep learning models can automatically learn relevant features from raw data, removing the need for handcrafted features.

• High expressiveness: Deep learning models can capture complex patterns and variations, leading to potentially better performance.

• State-of-the-art results: Deep learning has performed exceptionally in various recognition tasks, including gesture recognition [63], [73], [54], [57], [54], [76], [77].

Disadvantages of deep learning with End-to-End learning:

• Require more data: Deep learning models usually require large amounts of labelled data to generalize well.

• Require more computational resources: Training deep learning models can be computationally intensive and may require powerful hardware or cloud resources.

• Black-box nature: Deep learning models can be more complex to interpret than traditional ML approaches with handcrafted features [63], [73], [54], [57], [54], [78], [79], [80], [81].

In conclusion, traditional machine learning with handcrafted features can suit air writing numeral recognition when data is limited and interpretability is crucial. However, deep learning with end-to-end learning is the more common and state-of-the-art choice for larger datasets and higher recognition accuracy due to its ability to automatically learn complex patterns and features.

9. Research Gap and Limitations of Existing Systems

1. All the existing Air-writing numeral recognition systems use sensors/external devices except for very few works without sensors [55].

2. Previous Air-writing numeral recognition is script/language dependent [57]. In place of fingertip detection, a specific colour marker/ pen is used [55].

3. Few works are reported on numeral string recognition [55] with 85.27% accuracy.

4. Commonly spoken languages are addressed in Air-writing like Bengali, Oriya, Devanagari, and English [57].

5. A few methods like CNN, HMM, RNN, and LSTM were developed for multilingual Indian scripts [55], [57].

10. Conclusions and Future Work

This research presented a comprehensive review of the current work done in offline/online multilingual and air-writing multilingual numeral recognition with and without sensors. The systematic architecture of datasets, segmentation, feature extraction, and classification is provided with current applications and challenges. The paper reports that deep learning-based models have recently superseded conventional machine learning methods. This paper also focuses on the need for publicly available air-writing datasets and air-written real-time multilingual numeral string recognition challenges. It is concluded that only a little work is done for multilingual numeral recognition written in the air. Several researchers are working on that, but much work is still required for multilingual numeral recognition. The applications of multilingual numeral recognition written in the air are more. Nonetheless, expected methodology and challenges must be addressed, such as real-time hand pose and fingertip detection, variation in writing styles, strokes, etc.

In the future, this review can be effectively used in user identification in top agencies for security purposes using air-writing systems. In addition, the air-writing system can also be used in reservation counters of railways and flights, banking and online education systems, operation theatres, or COVID-like pandemic conditions without touching the devices.

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References

[1] K. C. Santosh, "Ai-driven tools for coronavirus outbreak: Need of active learning and cross-population train/test models on multitudinal/multimodal data," *Journal of Medical Systems*, vol. 44, 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:212743249

[2] J. Amankwah-Amoah, Z. Khan, G. R. Wood, and G. A. Knight, "Covid-19 and digitalization: The great acceleration," *Journal of Business Research*, vol. 136, pp. 602 – 611, 2021. [Online]. Available: https://api.semanticscholar.org/CorpusID:237493256

[3] T. Ghosh, S. Sen, S. M. Obaidullah, K. C. Santosh, K. Roy, and U. Pal, "Advances in online handwritten recognition in the last decades," *Comput. Sci. Rev.*, vol. 46, p. 100515, 2022. [Online]. Available: https://api.semanticscholar.org/CorpusID:253297413

[4] D. Ghosh, T. Dube, and A. P. Shivaprasad, "Script recognition—a review," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, pp. 2142–2161, 2010. [Online]. Available: https://api.semanticscholar.org/CorpusID:6611803

[5] P. B. Pati and A. G. Ramakrishnan, "Ocr in indian scripts: A survey," *IETE Technical Review*, vol. 22, pp. 217 – 227, 2005. [Online]. Available: https://api.semanticscholar.org/CorpusID:62493880

[6] R. Plamondon and S. N. Srihari, "On-line and off-line handwriting recognition: A comprehensive survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, pp. 63–84, 2000. [Online]. Available: https://api.semanticscholar.org/CorpusID:15782139

[7] P. Sahare and S. B. Dhok, "Script identification algorithms: a survey," *International Journal of Multimedia Information Retrieval*, vol. 6, pp. 211–232, 2017. [Online]. Available: https://api.semanticscholar.org/CorpusID:6723126

[8] S. Bag and G. Harit, "A survey on optical character recognition for bangla and devanagari scripts," *Sadhana*, vol. 38, pp. 133–168, 2013. [Online]. Available: https://api.semanticscholar.org/CorpusID:14396667

[9] J. M. Mantas, "An overview of character recognition methodologies," *Pattern Recognit.*, vol. 19, pp. 425–430, 1986. [Online]. Available: https://api.semanticscholar.org/CorpusID:33154342

[10] S. Mori, C. Y. Suen, and K. Yamamoto, "Historical review of ocr research and development," *Proc. IEEE*, vol. 80, pp. 1029–1058, 1992. [Online]. Available: https://api.semanticscholar.org/CorpusID:58021636

[11] V. K. Govindan and A. P. Shivaprasad, "Character recognition - a review," *Pattern Recognit.*, vol. 23, pp. 671–683, 1990. [Online]. Available: https://api.semanticscholar.org/CorpusID:29731301

[12] B. Zhu and M. Nakagawa, "Building a compact online mrf recognizer for large character set using structured dictionary representation and vector quantization technique," *2012 International Conference on Frontiers in Handwriting Recognition*, pp. 155–160, 2012. [Online]. Available: https://api.semanticscholar.org/CorpusID:12028050

[13] A. N. Azmi, D. Nasien, and S. M. H. Shamsuddin, "A review on handwritten character and numeral recognition for roman, arabic, chinese and indian scripts," *ArXiv*, vol. abs/1308.4902, 2013. [Online]. Available: https://api.semanticscholar.org/CorpusID:16629385

[14] M. Kumar, M. K. Jindal, and R. K. Sharma, "Review on ocr for handwritten indian scripts character recognition," 2011.

[15] H. Singh, R. K. Sharma, and V. P. Singh, "Online handwriting recognition systems for indic and non-indic scripts: a review," *Artificial Intelligence Review*, vol. 54, pp. 1525–1579, 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:221070843

[16] S. Mukherjee, S. A. Ahmed, D. P. Dogra, S. Kar, and P. P. Roy, "Fingertip detection and tracking for recognition of air-writing in videos," *ArXiv*, vol. abs/1809.03016, 2018. [Online]. Available: https://api.semanticscholar.org/CorpusID:52182184

[17] Y. Huang, X. Liu, L. Jin, and X. Zhang, "Deepfinger: A cascade convolutional neuron network approach to finger key point detection in egocentric vision with mobile camera," *2015 IEEE International Conference on Systems, Man, and Cybernetics*, pp. 2944–2949, 2015. [Online]. Available: https://api.semanticscholar.org/CorpusID:10044569

[18] P. K. Singh, R. Sarkar, and M. Nasipuri, "Offline script identification from multilingual indic-script documents: A state-of-the-art," *Comput. Sci. Rev.*, vol. 15, pp. 1–28, 2015. [Online]. Available: https://api.semanticscholar.org/CorpusID:20741179

[19] J. Memon, M. Sami, and R. A. Khan, "Handwritten optical character recognition (ocr): A comprehensive systematic literature review (slr)," *IEEE Access*, vol. 8, pp. 142 642–142 668, 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:209531740

[20] A. Bensefia, A. Nosary, T. Paquet, and L. Heutte, "Writer identification by writer's invariants," *Proceedings Eighth International Workshop on Frontiers in Handwriting Recognition*, pp. 274–279, 2002. [Online]. Available: https://api.semanticscholar.org/CorpusID:8259140

[21] L. G. Hafemann, R. Sabourin, and L. Oliveira, "Writer-independent feature learning for offline signature verification using deep convolutional neural networks," *2016 International Joint Conference on Neural Networks (IJCNN)*, pp. 2576–2583, 2016. [Online]. Available: https://api.semanticscholar.org/CorpusID:7685498

[22] G. X. Tan, C. Viard-Gaudin, and A. C. Kot, “Information retrieval model for online handwritten script identification,” *2009 10th International Conference on Document Analysis and Recognition*, pp. 336–340, 2009. [Online]. Available: https://api.semanticscholar.org/CorpusID:9782044

[23] G. S. Eskander, R. Sabourin, and E. Granger, “Hybrid writer-independent-writer-dependent offline signature verification system,” *IET Biom.*, vol. 2, pp. 169–181, 2013. [Online]. Available: https://api.semanticscholar.org/CorpusID:31604598

[24] Y. Nakamura and M. Kidode, “Online writer verification using kanji handwriting,” in *Multimedia Content Representation, Classification and Security*, 2006.

[25] X.-Y. Zhang, G. Xie, C.-L. Liu, and Y. Bengio, “End-to-end online writer identification with recurrent neural network,” *IEEE Transactions on Human-Machine Systems*, vol. 47, pp. 285–292, 2017. [Online]. Available: https://api.semanticscholar.org/CorpusID:6615543

[26] S. Dargan and M. Kumar, “Writer identification system for indic and non-indic scripts: State-of-the-art survey,” *Archives of Computational Methods in Engineering*, vol. 26, pp. 1283–1311, 2018. [Online]. Available: https://api.semanticscholar.org/CorpusID:126306739

[27] A. Rehman, S. Naz, and M. I. Razzak, “Writer identification using machine learning approaches: a comprehensive review,” *Multimedia Tools and Applications*, vol. 78, pp. 10 889–10 931, 2018. [Online]. Available: https://api.semanticscholar.org/CorpusID:52285511

[28] G. Cordasco, M. Buonanno, M. Faúndez-Zanuy, M. T. Riviello, L. Likforman-Sulem, and A. Esposito, “Gender identification through handwriting: an online approach,” *2020 11th IEEE International Conference on Cognitive Infocommunications (CogInfoCom)*, pp. 000 197–000 202, 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:226268366

[29] I. Razzak, I. Kamran, and S. Naz, “Deep analysis of handwritten notes for early diagnosis of neurological disorders,” *2020 International Joint Conference on Neural Networks (IJCNN)*, pp. 1–6, 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:221559354

[30] P. Maken and A. Gupta, “A method for automatic classification of gender based on text- independent handwriting,” *Multimedia Tools and Applications*, vol. 80, pp. 24 573 – 24 602, 2021. [Online]. Available: https://api.semanticscholar.org/CorpusID:233561892

[31] M. Rahmanian and M. A. Shayegan, “Handwriting-based gender and handedness classification using convolutional neural networks,” *Multimedia Tools and Applications*, pp. 1–24, 2021. [Online]. Available: https://api.semanticscholar.org/CorpusID:230719001

[32] N. Tagougui, M. Kherallah, and A. M. Alimi, “Online arabic handwriting recognition: a survey,” *International Journal on Document Analysis and Recognition (IJDAR)*, vol. 16, pp. 209–226, 2013. [Online]. Available: https://api.semanticscholar.org/CorpusID:6972944

[33] A. Indian and K. Bhatia, “A survey of offline handwritten hindi character recognition,” *2017 3rd International Conference on Advances in Computing,Communication & Automation (ICACCA) (Fall)*, pp. 1–6, 2017. [Online]. Available: https://api.semanticscholar.org/CorpusID:5062188

[34] A. Mirza, O. Zeshan, M. Atif, and I. Siddiqi, “Detection and recognition of cursive text from video frames,” *EURASIP Journal on Image and Video Processing*, vol. 2020, pp. 1–19, 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:221357329

[35] U. Pal and B. B. Chaudhuri, “Identification of different script lines from multi-script documents,” *Image Vis. Comput.*, vol. 20, pp. 945–954, 2002. [Online]. Available: https://api.semanticscholar.org/CorpusID:11049529

[36] R. Gopakumar, N. V. Subbareddy, K. Makkithaya, and U. D. Acharya, “Zone-based structural feature extraction for script identification from indian documents,” *2010 5th International Conference on Industrial and Information Systems*, pp. 420–425, 2010. [Online]. Available: https://api.semanticscholar.org/CorpusID:16143968

[37] P. PrasanthKumar and E. D. Dileesh, “Word level script and language identification for unconstrained handwritten document images,” *2014 3rd International Conference on Eco-friendly Computing and Communication Systems*, pp. 14–18, 2014. [Online]. Available: https://api.semanticscholar.org/CorpusID:14359087

[38] V. Singhal, N. Navin, and D. Ghosh, “Script-based classification of hand-written text documents in a multilingual environment,” *Proceedings. Seventeenth Workshop on Parallel and Distributed Simulation*, pp. 47–54, 2003. [Online]. Available: https://api.semanticscholar.org/CorpusID:36214643

[39] C. V. Jawahar, M. N. S. S. K. P. Kumar, and S. S. R. Kiran, “A bilingual ocr for hindi-telugu documents and its applications,” *Seventh International Conference on Document Analysis and Recognition, 2003. Proceedings.*, pp. 408–412 vol.1, 2003. [Online]. Available: https://api.semanticscholar.org/CorpusID:5341645

[40] M. Benjelil, S. Kanoun, R. Mullot, and A. M. Alimi, “Arabic and latin script identification in printed and handwritten types based on steerable pyramid features,” *2009 10th International Conference on Document Analysis and Recognition*, pp. 591–595, 2009. [Online]. Available: https://api.semanticscholar.org/CorpusID:11725256

[41] L. B. Zhou, X. Ping, E. Zheng, and L. . B. Guo, “Script identification based on wavelet energy histogram moment features,” *IEEE 10th INTERNATIONAL CONFERENCE ON SIGNAL PROCESSING PROCEEDINGS*, pp. 980–983, 2010. [Online]. Available: https://api.semanticscholar.org/CorpusID:14109356

[42] I. Moalla, A. Elbaati, A. A. Alimi, and A. Benhamadou, “Extraction of arabic text from multilingual documents,” *IEEE International Conference on Systems, Man and Cybernetics*, vol. 4, pp. 5 pp. vol.4–, 2002. [Online]. Available: https://api.semanticscholar.org/CorpusID:61005048

[43] S. B. Moussa, A. Zahour, A. BenAbdelhafid, and A. M. Alimi, “Fractal-based system for arabic/latin, printed/handwritten script identification,” *2008 19th International Conference on Pattern Recognition*, pp. 1–4, 2008. [Online]. Available: https://api.semanticscholar.org/CorpusID:16606016

[44] A. Elgammal and M. A. Ismail, “Techniques for language identification for hybrid arabic-english document images,” *Proceedings of Sixth International Conference on Document Analysis and Recognition*, pp. 1100–1104, 2001. [Online]. Available: https://api.semanticscholar.org/CorpusID:17750786

[45] S. Kanoun, A. Ennaji, Y. Lecourtier, and A. M. Alimi, “Script and nature differentiation for arabic and latin text images,” *Proceedings Eighth International Workshop on Frontiers in*

Handwriting Recognition, pp. 309–313, 2002. [Online]. Available: https://api.semanticscholar.org/CorpusID:2944499

[46] A. Busch, W. W. Boles, and S. Sridharan, "Texture for script identification," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, pp. 1720–1732, 2005. [Online]. Available: https://api.semanticscholar.org/CorpusID:9448504

[47] R. Sharma and B. Kaushik, "Offline recognition of handwritten indic scripts: A state-of-the-art survey and future perspectives," *Comput. Sci. Rev.*, vol. 38, p. 100302, 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:224851201

[48] P. B. Pati and A. G. Ramakrishnan, "Word level multi-script identification," *Pattern Recognit. Lett.*, vol. 29, pp. 1218–1229, 2008. [Online]. Available: https://api.semanticscholar.org/CorpusID:29800201

[49] M. Kumar and S. R. Jindal, "A study on recognition of pre-segmented handwritten multi-lingual characters," *Archives of Computational Methods in Engineering*, vol. 27, pp. 577–589, 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:127347634

[50] U. Pal and B. B. Chaudhuri, "Script line separation from indian multi-script documents," *Proceedings of the Fifth International Conference on Document Analysis and Recognition. ICDAR '99 (Cat. No.PR00318)*, pp. 406–409, 1999. [Online]. Available: https://api.semanticscholar.org/CorpusID:32288783

[51] "Ponemos a tu disposicion el giving tuesday toolkit 2021," 2021.

[52] S. Madhvanath, D. Vijayasenan, and T. M. Kadiresan, "Lipitk: a generic toolkit for online handwriting recognition," *ACM SIGGRAPH 2007 courses*, 2007. [Online]. Available: https://api.semanticscholar.org/CorpusID:1899024

[53] P. K. Singh, S. Das, R. Sarkar, and M. Nasipuri, "Handwritten mixed-script recognition system: A comprehensive approach," in *International Conference on Frontiers in Intelligent Computing: Theory and Applications*, 2016.

[54] P. Roy, S. Ghosh, and U. Pal, "A cnn based framework for unistroke numeral recognition in air-writing," *2018 16th International Conference on Frontiers in Handwriting Recognition (ICFHR)*, pp. 404–409, 2018. [Online]. Available: https://api.semanticscholar.org/CorpusID:56597549

[55] A. Rahman, P. Roy, and U. Pal, "Continuous motion numeral recognition using rnn architecture in air-writing environment," in *Asian Conference on Pattern Recognition*, 2019.

[56] H. Ishida, T. Takahashi, I. Ide, and H. Murase, "A hilbert warping method for handwriting gesture recognition," *Pattern Recognit.*, vol. 43, pp. 2799–2806, 2010. [Online]. Available: https://api.semanticscholar.org/CorpusID:15681779

[57] C.-H. Hsieh, Y.-S. Lo, J.-Y. Chen, and S. Tang, "Air-writing recognition based on deep convolutional neural networks," *IEEE Access*, vol. 9, pp. 142 827–142 836, 2021. [Online]. Available: https://api.semanticscholar.org/CorpusID:240004116

[58] C. Amma, M. Georgi, and T. Schultz, "Airwriting: Hands-free mobile text input by spotting and continuous recognition of 3d-space handwriting with inertial sensors," *2012 16th International Symposium on Wearable Computers*, pp. 52–59, 2012. [Online]. Available: https://api.semanticscholar.org/CorpusID:9626619

[59] P. Krejov and R. Bowden, "Multi-touchless: Real-time fingertip detection and tracking using geodesic maxima," *2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*, pp. 1–7, 2013. [Online]. Available: https://api.semanticscholar.org/CorpusID:14394970

[60] H. Liang, J. Yuan, and D. Thalmann, "3d fingertip and palm tracking in depth image sequences," *Proceedings of the 20th ACM international conference on Multimedia*, 2012. [Online]. Available: https://api.semanticscholar.org/CorpusID:15157295

[61] M. D. L. Gorce, D. J. Fleet, and N. Paragios, "Model-based 3d hand pose estimation from monocular video," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, pp. 1793–1805, 2011. [Online]. Available: https://api.semanticscholar.org/CorpusID:215901625

[62] D. Tang, H. J. Chang, A. Tejani, and T.-K. Kim, "Latent regression forest: Structured estimation of 3d hand poses," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, pp. 1374–1387, 2017. [Online]. Available: https://api.semanticscholar.org/CorpusID:27301176

[63] T. Lee and T. Höllerer, "Handy ar: Markerless inspection of augmented reality objects using fingertip tracking," *2007 11th IEEE International Symposium on Wearable Computers*, pp. 83–90, 2007. [Online]. Available: https://api.semanticscholar.org/CorpusID:5247092

[64] X. Zhang, Z. Ye, L. Jin, Z. Feng, and S. Xu, "A new writing experience: Finger writing in the air using a kinect sensor," *IEEE MultiMedia*, vol. 20, pp. 85–93, 2013. [Online]. Available: https://api.semanticscholar.org/CorpusID:8425969

[65] A. Mittal, A. Zisserman, and P. H. S. Torr, "Hand detection using multiple proposals," in *British Machine Vision Conference*, 2011.

[66] Y. Zhuang, Q. Liu, C. Qiu, C. Wang, F. Ya, A. Sabbir, and J. Yan, "A handwritten chinese character recognition based on convolutional neural network and median filtering," *Journal of Physics: Conference Series*, vol. 1820, 2021. [Online]. Available: https://api.semanticscholar.org/CorpusID:233820742

[67] S. Palaiahnakote, S. di Baja, G., L. Wang, and W. Q. Yan, "5th asian conference, acpr 2019," *5th Asian Conference, ACPR 2019*, pp. 1–450, 2019. [Online]. Available: 10.1007/978-3-030-41404-7

[68] G. Kumar, "Analytical review of preprocessing techniques for offline handwritten character recognition," *International Journal of Advances in Engineering Sciences*, vol. 3, pp. 14–22, 2013. [Online]. Available: https://api.semanticscholar.org/CorpusID:59763813

[69] A. G. Ramakrishnan and K. B. Urala, "Global and local features for recognition of online handwritten numerals and tamil characters," in *MOCR '13*, 2013.

[70] F. A. Abir, M. A. Siam, A. Sayeed, M. A. M. Hasan, and J. Shin, "Deep learning based air-writing recognition with the choice of proper interpolation technique," *Sensors (Basel, Switzerland)*, vol. 21, 2021. [Online]. Available: https://api.semanticscholar.org/CorpusID:245291391

[71] B. Saez-Mingorance, J. Mendez-Gomez, G. Mauro, E. C. Morales, M. P. Cuéllar, and D. P. Morales-Santos, "Air-writing character recognition with ultrasonic transceivers," *Sensors (Basel, Switzerland)*, vol. 21, 2021. [Online]. Available: https://api.semanticscholar.org/CorpusID:239616725

[72] H. Zhang, L. Chen, Y. Zhang, R. Hu, C. He, Y. Tan, and J. Zhang, "A wearable real-time character recognition system based on edge computing-enabled deep learning for air-writing," *J. Sensors*, vol. 2022, pp. 1–12, 2022. [Online]. Available: https://api.semanticscholar.org/CorpusID:248607351

[73] X. Qu, W. Wang, K. Lu, and J. Zhou, "Data augmentation and directional feature maps extraction for in-air handwritten chinese character recognition based on convolutional neural network," *Pattern Recognit. Lett.*, vol. 111, pp. 9–15, 2018. [Online]. Available: https://api.semanticscholar.org/CorpusID:52011140

[74] M. S. Alam, K.-C. Kwon, and N. Kim, "Trajectory-based air-writing character recognition using convolutional neural network," *2019 4th International Conference on Control, Robotics and Cybernetics (CRC)*, pp. 86–90, 2019. [Online]. Available: https://api.semanticscholar.org/CorpusID:215740240

[75] E. R. S, K. C. K, M. V. P, V. M. K, S. S. K, and P. M. S, "A survey on air writing character recognition and translation," *International Journal of Engineering Applied Sciences and Technologies*, 2023. [Online]. Available: https://www.ijeast.com/papers/36-46,%20Tesma0712,IJEAST.pdf

[76] Heena and S. Ranjan, "A systematic study of various fingertip detection techniques for air writing using machine learning," *ArXiv*, vol. abs/2306.04332, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:259095976

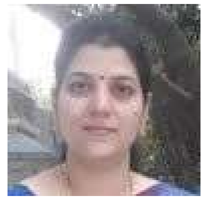
[77] M. Jabde, C. H. Patil, A. Vibhute, and S. Mali, "Comparative study of machine learning and deep learning classifiers on handwritten numeral recognition," *International Symposium on Intelligent Informatics. Singapore: Springer Nature Singapore, 2022*, 2022. [Online]. Available: https://link.springer.com/chapter/10.1007/978-981-19-8094-7_10

[78] Y. Luo, W. Ke, and C.-T. Lam, "Wearable real-time air-writing system employing knn and constrained dynamic time warping," *2023 IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1–6, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:258641608

[79] J. B. Jung, S. Lim, J. Kim, and S.-C. Kim, "Digit recognition using fmcw and uwb radar sensors: A transfer learning approach," *IEEE Sensors Journal*, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:259687388

[80] C. H. Patil, R. Zope, and M. Jabde, "Comparative study of multilingual text detection and verification from complex scene," *2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, pp. 903–910, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:259123079

[81] C. H. Patil and S. M. Mali, "Marathi handwritten numeral recognition using zernike moments and fourier descriptors," 2015.



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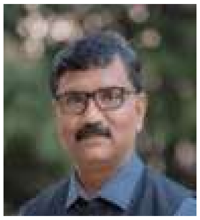

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