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Usage of deep learning in recent applications

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ABSTRACT

Purpose: Deep learning is a predominant branch in machine learning, which is inspired by the operation of the human biological brain in processing information and capturing insights. Machine learning evolved to deep learning, which helps to reduce the involvement of an expert. In machine learning, the performance depends on what the expert extracts manner features, but deep neural networks are self-capable for extracting features.

Design/methodology/approach: Deep learning performs well with a large amount of data than traditional machine learning algorithms, and also deep neural networks can give better results with different kinds of unstructured data.

Findings: Deep learning is an inevitable approach in real-world applications such as computer vision where information from the visual world is extracted, in the field of natural language processing involving analyzing and understanding human languages in its meaningful way, in the medical area for diagnosing and detection, in the forecasting of weather and other natural processes, in field of cybersecurity to provide a continuous functioning for computer systems and network from attack or harm, in field of navigation and so on.

Practical implications: Due to these advantages, deep learning algorithms are applied to a variety of complex tasks. With the help of deep learning, the tasks that had been said as unachievable can be solved.

Originality/value: This paper describes the brief study of the real-world application problems domain with deep learning solutions.

Keywords: Conceptual based information retrieval, Ontology, Semantic search

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METHODOLOGY OF RESEARCH, ANALYSIS AND MODELLING

1. Introduction

Deep learning helps us in day-to-day activities like shopping, language translation, voice recognition, etc., by imitating human skills. Deep learning first appeared in the 1950s, but because of a lack of processing capacity, it was not well known and accepted [1]. Massive amounts of data and powerful graphics processing units have allowed deep learning to become popular. Deep neural networks, which include many hidden layers between the input and output layers, are used in deep learning. These networks can either get supervised training or unsupervised training. In supervised learning, the processing system generates an output based on input data that is then matched to the actual output, yielding an error. The learning aim is to use a technique to decrease this inaccuracy and adjust the input variables in each iterative process. The model keeps learning until it achieves the necessary efficiency. When the intended outcome is uncertain, unsupervised learning aims to find the data's undiscovered pattern. Unsupervised learning is therefore not relevant to problems involving regression and classification.

Numerous deep learning model variants are utilized for varied applications [2]. One might select a primary model that refers to the application. A multilayer perceptron is A traditional network with several hidden layers. It may be used for classification and regression issues and trained on various dataset types. Instead of creating the filter by hand, CNN can learn a variety of filters, which benefits in finding the crucial data features. CNN is mostly used for image-related issues. RNNs can preserve an internal state or memory from prior inputs to compute the output from the present input, taking into account the prior output. This recurring activity helps the network in applications that involve gathering sequence data. They are frequently employed in text generation and language modeling. Boltzmann machine (BM) is a collection of nodes connected by links that can result in stochastic decisions on whether to react or not. These can be utilized to solve challenges involving combinatorial optimization. Encoding, coding, and decoding are all steps of an auto-encoder. Input is supplied into the encoder, which compresses it and creates a code; the encoder then decompresses or reconstructs. By using unsupervised learning to create a compressed form, auto-encoders aid in dimensionality reduction. Data retrieving and compressing tasks require auto-encoders. Figure 1 represents the hierarchy of AI, ML, and deep learning in material science. Here, the term SMILES describes a simplified molecular input line entry system. Some image modalities include scanning transmission electron microscopy (STEM), scanning probe tunneling microscopy (STM), and scanning electron microscopy (SEM). In the Figure, Xray Diffraction (XRD), X-ray Absorption Near Edge Spectroscopy (XANES), and X-ray Absorption Spectroscopy (XAS) are some spectroscopy models.

Deep learning was applied in many different domains. A subfield of computer science called computer vision aids machines in comprehending visual information like pictures and video. Deep learning is emerging as a crucial tool for computer vision issues, including image categorization, object identification, picture reformation, face identification, image synthesis, etc. [3]. Deep learning networks such as convolutional neural networks utilize sufficient computer power and data to perform accurately. There is competition among ResNet, VGGNet, GoogLeNet, LeNet-5, and AlexNet for CNN designs or computer vision issues [4]. Electrical engineering's subfield of signal processing entails generating, manipulating, and changing signals acquired from a transducer. Compared to conventional signal processing techniques, CNN designs and recurrent networks like LSTM produce superior outcomes [5]. The healthcare and medical sectors have been significantly impacted by deep learning. It can be of great use to medical professionals due to its outstanding performance in evaluating images like X-rays and MRIs [6].

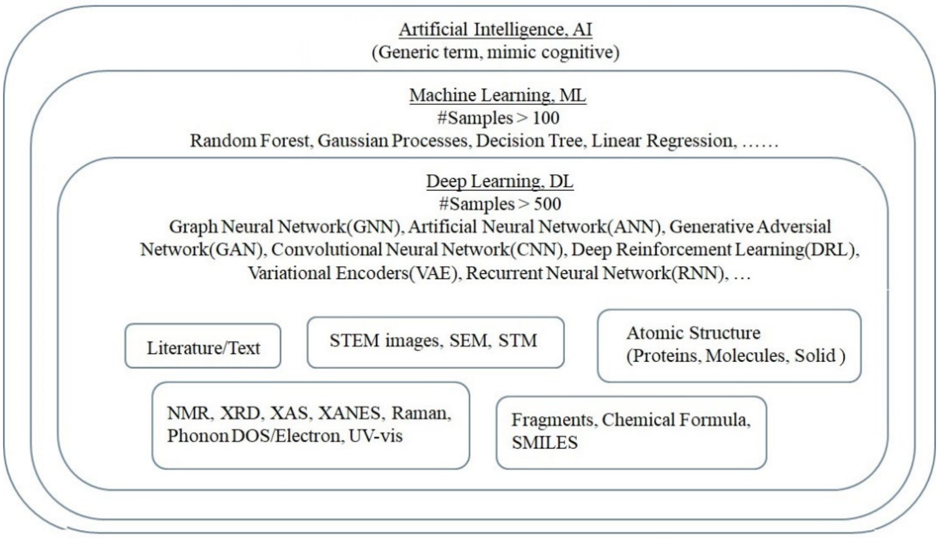

Fig. 1. Applications of AI, ML, and Deep Learning in Material Science

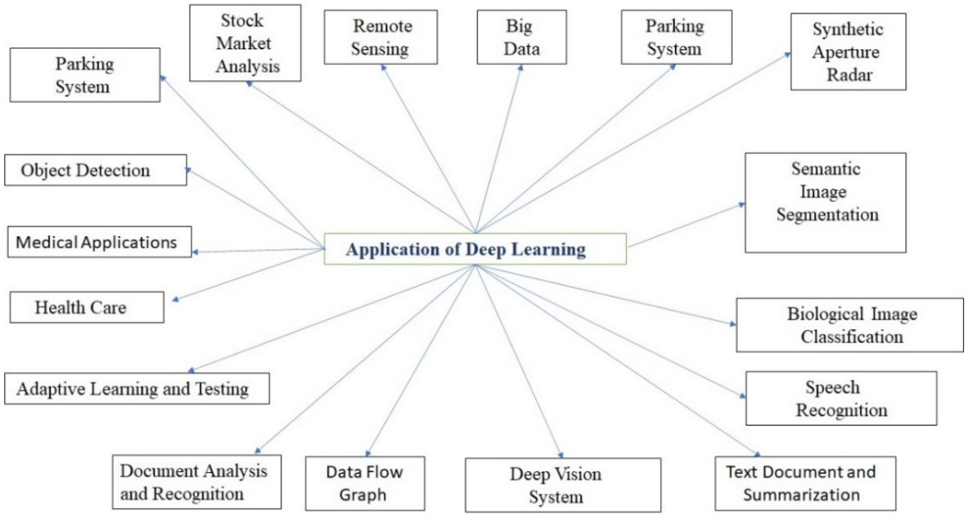

Fig. 2. Different applications of Deep Learning

Current pandemic COVID-19 research focuses on developing vaccines and using deep learning to diagnose cases. Forecasting is the practice of making future predictions based on the evaluation of current and past facts. A more robust forecasting framework made possible by deep learning facilitates human strategizing and decision-making. Conventional time series forecasting approaches rely on the linear approach; however, deep learning approaches may be trained to create complicated input-output mappings. The forecasting of time series is made efficiently using CNN and LSTM. Handling and monitoring an aircraft's or a car's movements from its launching point to its destination is the subject of the study of navigation. The popularity of self-driving automobiles indicates a rise in demand for these vehicles [7]. Cybersecurity is a sector that comprises technology solutions that guard computers, networks, and essential data against illegal use and loss. In this digital environment, people are subject to numerous cyber-attacks and cybercrimes. Excellent performances are shown via deep learning-based virus detection, spam detection, and network traffic analysis. The remainder of this presentation provides an overview of contemporary deep learning techniques applied to practical issues. We identify the problem that has to be resolved, the strategy used, and the results for each method. Figure 2 represents different applications in today's era of IOT and big data.

2. Contributions of deep learning

2.1. Medical

Due to their complicated processes, traditional health diagnostic tools are inconvenient for real-time analysis. Bhaskar et al. introduced a novel technique for detecting kidney disease, including CNN and SVM classifiers [8]. Since saliva contains a symptom particle and is readily available, saliva samples are used for identification rather than blood. To track kidney health, serum urea and creatinine levels might be tested. Recent research has shown a relationship between serum and salivary urea levels [9]. Salivary urea levels that are higher than usual might reveal faulty kidney function. Here, urea is hydrolyzed using urease enzymes. A semiconducting sensor monitors the amount of ammonia after this enzymatic process produces ammonia gas. The MQ-type ammonia gas reader, an Arduino controller, and a specially made sensing chamber that includes the sensor makes up the monitoring module's hardware arrangement. While sampling, the sample is deposited into the gas detecting chamber's input entrance. The sensor's conductance fluctuates according to how much ammonia gas is being generated. This conductivity variability is sent to the sensor unit's output as an analog signal. The features are automatically extracted from the sensor unit's output using a CNN-SVM-based technique. The CNN is adapted in this case to analyze the 1D signal. Convolution is applied to the sensor output signal utilizing the kernel. The resulting feature map is described in equation (1).

$$ci(n) = \sum_{m=-p}^{p} x(m+1)\, k(q-m+1) \quad (1)$$

Convolution is executed first, then a pooling function that down-samples the feature map, with x being the input signal and k being the kernel function, both of which have lengths of p and q. To acquire the reduced feature map, convolution and pooling are iteratively applied. In this, a five-layered CNN is utilized, with convolution performed using a Gaussian kernel. This article suggests an SVM classifier as an alternative to a fully-connected network classifier. The features are classified using an SVM classifier with an RBF (Radius Basis Function) kernel. The samples may be classified using this approach with an accuracy of 98.04 percent.

Hookworms are parasites that feed on blood and are frequently found in the human intestine. Untreated conditions like anemia, which can cause heart failure, can negatively influence health. According to reports, there have been more than 600 million infections globally [10]. He et al. presented the first architecture for wireless capsule endoscopy imaging deep hookworm diagnosis [11]. Two CNN networks contribute to making up a procedure; one is for edge extraction, and the other is for classifying hookworms. The swallowed wireless capsule endoscopy is used to gather the intestinal pictures. The equipment may capture about 50,000 photos of the intestine. An expert's analysis of the damaged spot can be time-consuming; these photos also have issues with quality, lighting, and orientation. The core of these two leveled fusion structures is its edge pooling phase. A multi-scale dual paired filter is exposed to an edge map generated by an edge extraction network to determine the hookworm's tubular network. For detecting edges, the holistically nested edge detection (HED) approach has better accuracy than other methods. The HED comprises several side results from a hierarchy of deep neural networks. In this, five side output modules are specified. Lower level side output has more edge information hence second and third level side output is gathered for edge detection.

Due to the Gaussian form of the hookworm's cross-section, MDMF is a framework that may be used to detect the tubular parts of the hookworm. Consequently, adding a filter to the image causes a greater reaction. As a result, the MDMF mutes the noise and concentrates on the hookworm's edge. The tubular maps are included in the classification network via edge pooling and regularised edge pooling. The hookworm recognition network is constructed using nine sparsely connected inception designs to accommodate overfitting and computing resources. In matching the spatial dimension of the tubular area map and hookworm classifying feature map, max-pooling layers are employed before the edge pooling procedure. Studies on the WCE image dataset, which contains 440K pictures, demonstrate the effectiveness of this system in clinical applications.

2.2. Forecasting

Forecasting household load is a crucial part of planning. Forecasting load is a complex undertaking due to the instability of load profiles and their ambiguity. These uncertainties are eliminated by conventional techniques, including load aggregation, customer categorization, and spectrum analysis. Shi et al. (2018) provide the solution to this issue in their research "Deep Learning for Household Load Forecasting A Novel Pooling Deep RNN" [12]. The approach comprises two phases: the initial load profile pooling phase and the STFL with a deep learning phase at the end. The pooling technique was used to take into account STLF's substantial challenges, including the overfitting and high levels of inherent uncertainty. Overfitting occurs when there are too many layers in neural networks and not enough load profile data. The pooling stage increases the volume of data and lowers overfitting.

The load dataset variety can be improved by combining the load profiles of the customers. Every 30 minutes, data on daily load profiles are gathered from 48 value locations with smart meters. In pooling, a long vector combines the load profiles of consecutive dates. There are three phases in the load profile pool. In the first phase, a dummy variable is assigned to the demand data to determine its customer id; after that, the train and test sets are created by dividing the demand data for each consumer. Lastly, the training and testing set is batch-combined to generate training and testing pools for each consumer. Testing and training are done afterward. DRNN is first initialized for training and trains the network until load loss converges. Each training session involves feeding a batch of size B with the dimensionality B x (sequencing size), and the result is B x (result sequencing size). To obtain the optimal point quickly in the early stages and enhance efficiency at higher epochs, batch size B is raised. The loss function is expressed as (2), where ya is the actual output and yp is the output from the training.

$$Loss = \sqrt[2]{\frac{1}{O}\,\frac{1}{B}\,\sum_{I=1}^{O}\sum_{J=1}^{B}(y_p - y_a)^2} \tag{2}$$

TensorFlow is used to develop the deep learning framework. The processes included in implementing a program are data preprocessing, pooling, sampling, training, and benchmarking. This approach outperforms other methods like SVR, RNN, and ARIMA.

2.3. Navigation

The undersea situation makes it challenging to recognize acoustic targets since it is unexpected and dynamic. Traditional machine learning techniques need significant human labor, from feature extraction and selection through classifier design. Traditional approaches exhibit poor generalization when dealing with enormous volumes of complicated data. For underwater vehicle navigation, "A Novel Cooperative Deep Learning approach for Underwater Acoustic Target Detection" has been proposed [13]. In this, ship radiated noise is classified using a cooperative deep learning framework. Deep Auto Encoder (DAE) and Deep Long Short-Term Memory (DLSTM) structures are used in this technique. The LSTM system aids in the analysis of the time-series signal, while the DAE helps to compress the input data. This process is divided into two phases; first, an LSTM-based DAE system with an encoder and decoder is designed.

The data is compressed using an encoder to fit it into a smaller dimension with one or more LSTM layers. The input data is reconstructed by the decoder using at minimum one layer of LSTM. The DLSTM classifier in the DAE network is pre-trained using an LSTM-based DAE system. The network is trained through good reconstruction of data that is similar to the input data. By eliminating unnecessary and duplicate information, this network improves the process of retrieving the fundamental properties of incoming data. A softmax layer and the already pre-trained encoder layer are combined in the following steps to create a cooperative DLSTM system. The LSTM is used to train the new collaboration network on the variability and core features. Oceans Network Canada Observatory and ship radiated noise data experiments are designed to examine the suggested technique. Data on a noisy environment is gathered when there are no ships within a 5-kilometer range of the hydrophone. The noisy sample is sampled at a frequency of 32 kHz. The utilized dataset has a total runtime of 21.7 hours, which is also divided into 13.7 hours and 8 hours of training and testing, respectively. When compared to the DAE system and DLSTM system, which are used as comparisons, this approach has a 90% accuracy rate.

The most challenging part of a flight is landing. Due to poor weather or technological failure, humans have seen several landing mishaps. Using unmanned aerial vehicles (UAV) in field surveys, military operations, urban management, monitoring, and rescuing has become prevalent. A computing system controls UAVs autonomously after analyzing the aerial image captured by the onboard sensors. Techniques for perfect runway identification based on visual acuity should be used for safe landings. Akbar et al. (2019) suggested runway identification and localization techniques [14]. A classifier is initially created to identify the runway in the aerial image, and then traditional and deep learning techniques are used to locate the identified runways. This research utilized a remote sensing dataset with many classes since it is not a helpful approach but is adequate to discover binary runway classifications. Images input are mean normalized and adjusted to 224×224. Three classifiers are developed from ResNet, VGGNet, and DenseNet for feature extraction, and an output softmax function is added. ResNet is chosen as the top performer among others based on its efficiency. Runway localization uses CNN methods and line object recognition like the Hough transform and linear segment analyzer. For segmenting, masked R-CNN is trained in the coco dataset. The data sets utilized are 700 photos of the class runway using Labeling Me. One hundred photos the experimenter created were collected from Google Earth for training and testing. This approach utilizes deep learning techniques to discard the requirement for manually created features and obtained a satisfactory IOU of 0.8.

2.4. Natural language processing

The web has a vast content volume; thus, separating the helpful or pertinent text from the massive content is crucial. Parvathi & Jyothis (2018) utilized CNN to recognize the relevant text in a text document [15]. Data is initially delivered to the preprocessing phase, which includes spam identification and steaming. Making tokens and stemming is done using the Natural Language Toolkit (NLTK). The extraction of features is done in the following phase. The collected relevant data is categorized using a neural network classification approach to obtain the result. Twenty documents and four categories – education, farewell, sandwich, and greetings – are selected for classifying essential text documents. The suggested method demonstrates an improved approximative accuracy.

For classifying the text, Bai proposed approach utilizes the combination of LSTM and convolution concepts [16]. Convolutional layers are used in the initial stage to extract preliminary characteristics. The text data is used to train several convolutional filters that extract local information. Long time-dependent sequences can be learned using the three gates available in LSTM cells. The attention process generates a deep feature-containing attention probabilistic model. The softmax layer receives these deep features from LSTM and attention network to classify. The suggested procedures are shown in Figure 3. The data set utilized for simulating is the Chinese Opinion Assessment Microblog data set, which includes 2426 microblogs for testing and 9423 for training. The verification of the efficiency of the proposed technique is compared with RNN, CNN, and LSTM. It demonstrates improved LSTM performance.

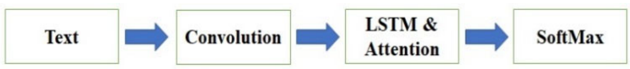

Fig. 3. Text classification block diagram

Using the Bi-LSTM-CNN approach, Li et al. (2018) analyzed text classification [17]. The process contains a local and global feature layer, a softmax layer, and a Bi-LSTM layer. The Bi-LSTM layer is made up of a word vector with right and left contexts. The word vector is trained using Word2Vec. The word vector was trained using a continual bag of words. The bidirectional LSTM model consists of both the forward and reverse ordered semantics.

Right, and left contexts are combined using convolution to provide an expression for the first context word. The text is transformed into fixed-length vectors using a Max pooling layer once the tanh activation function has been applied. THUCNews is partitioned into training and testing subsets. 65000 coropa are partitioned such that 76% of the instances are used for training, 15% for testing, and the rest for verification purposes. This approach is examined against other models like LSTM, CNN, and SVM. The suggested model increased classifier accuracy by 0.84%.

2.5. Signal processing

When processing an electrocardiogram (ECG), it is crucial to efficiently de-noise the signals because they are made up of noise. Arsene et al. proposed two deep learning-based de-noising methods using a conventional wavelet approach [18]. The LSTM-based and CNN-based methods are deep learning models that are evaluated using wavelet techniques. This study evaluated a CNN method with six 2D convolutional layers and 36 filters with kernel dimensions of 19x1 and 30000x1x1 was evaluated. Convolutional layers are followed by a batch normalization layer, whose result is input into a rectified linear unit (RELU) and an average pooling layer that decreases dimensionality. Before the output layer, a completely linked layer is utilized. The regression layer is the output layer used to produce the ECG de-noised data. The second model is composed of LSTM layers; it has two LSTM layers with 140 hidden units in each layer and a 30000x1-dimensional sequence input layer. These hidden units make use of the RELU activation mechanism. A regression output layer and a fully connected layer are added to the output. The CNN-based approach may remove high-level noise from the ECG, according to the results of the final de-noising procedure, which is wavelet-based on the empirical Bayesian technique for comparing. In contrast to the LSTM-based approach, CNN offers superior results that save time.

Pak et al. (2019) proposed a method for calculating accurate noise evaluation units to compensate for the annoyance of aircraft noise using the CNN model [19]. The dataset comprises 100,000 mp3 recordings of noise that have been manually categorized from five separate noise sensors installed on the roofs of buildings close to Korea's Jeju Airport Terminal. The noise signal is isolated into feature vectors using Mel-frequency cepstral coefficients (MFCC). The produced feature vector and the mel-spectrogram images are both necessary forms of data. 2 types of data are required: the obtained feature vector and the other is the mel-spectrogram image. Librosa module in python is used for converting the sound signal to mel-spectrogram. After conversion, the data is split into train and test in ratio 7:3. The CNN model consists of 5 convolutional layers, three pooling layers, and a fully connected layer. The convolutional layer has a RELU activation function with a 3x3 sized kernel, 1st dense layer after the flatten layer has activation of tanh with a dropout of 0.25, and the final layer has a softmax activation function. This method is cost-effective when the MFCC feature vectors are applied for input; the model gives an accuracy of 99.84% with an FP rate of 0.16 and an FN rate of 0%.

2.6. Autonomous vehicle

For the safe functioning of autonomous vehicles, fault detection is essential. Failure to accurately and immediately detect faults may lead to vehicle breakdown or even accidents. Ren et al. (2019) proposed a general framework developed for Fault detection in the system dynamics model [20]. They collected input-output data from a multi-wheeled autonomous vehicle to build a system model. They used the MATLAB System identification toolbox to generate the dynamic system model. The proposed framework consists of a system model, continuous wavelet transforms (CWT), and a deep neural network. The input to the continuous wavelet transform is generated from the system model by supplying information. The CWT produces two-dimensional images from one-dimensional signals. Figure 4 shows the fault detection framework. These images having size (512×512) are given input to the ten layered deep neural networks. They have tested the proposed deep neural network, and wavelet transform technique giving separate 500 defected and normal images, and established this method can effectively use for fault detection.

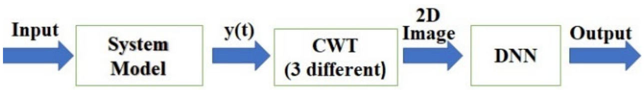

Fig. 4. Fault detection framework

Sanil et al. (2020) identified obstacles and their avoidance using CNN [21]. The miniature self-driving car consists of 2 DC motors which the L293d motor driver controls. They perform acceleration and steering movements of wheels. Raspberry pi 3B is used to manage the car movement and process the information. Figure 5 shows the operational framework of designing a self-driving car, in which a camera connected in front of the vehicle is responsible for capturing images for training. Input images and direction commands are collected and trained in the neural network model. The CNN model consists of 2 convolutional layers. 1st convolutional layer contains 32 filters of dimension 3×3, then a dropout layer with the dropout rate of 20% is applied.

Next convolutional layer of 64 filters having dimension 3×3. Then a max-pooling layer of size 2×2 is applied with a dropout layer of 20%. The network is flattened to 1dimensional and applied to a dense layer having 128 neurons; the activation function used in this layer is RELU. The final output dense layer consists of 4 units with softmax activation. The output indicates the vehicle's direction of steering and movement (forward, stop, left, and right). During training, an accuracy of 86.6% is achieved. Car driving pattern successfully detects and avoid obstruction, and it requires more data and training for new scenarios.

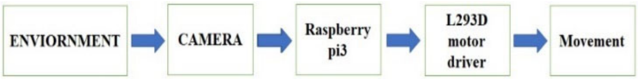

Fig. 5. Operational framework of self-driving car

2.7. Computer vision

Facial expression is the natural way of communicating emotions. Through facial expression recognition (FER), the deep feelings of a person or a crowd can be understood. Zhang et al., (2019) proposed a method for facial expression recognition using a hybrid deep learning method on videos [22]. Figure 6, shows the FER block diagram. Inputs to the CNN are fixed-sized, so the video sample is divided into segments. Two stream CNN are used for special temporal feature extraction. Inputs to the temporal CNN are optical flow images constructed from consecutive frames. Input into the special CNN is cropped spatial image. Both CNN in the network are fine-tuned from the pre-trained VGG16 network, and they are applied to the deep belief network. A two-step strategy is adopted to train the RBM model. The method is experimented with using three public facial expression data sets. The output results show that the method outperforms the state of the arts on the experimental data sets.

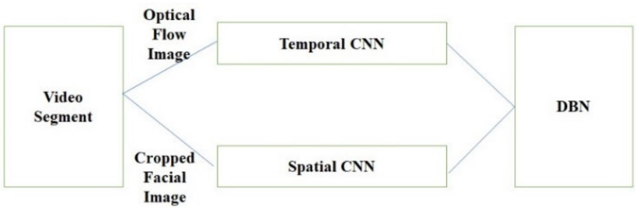

Fig. 6. Block diagram of FER method

Image feature matching is a primary feature used in computer vision for image retrieval and object tracking. Irrespective of geometric transformation or illumination, the image should be appropriately matched. Liu et al., (2018) adopted CNN based deep learning model for image feature point matching [23]. The adopted CNN structure has seven convolutional layers. The final layer having a kernel size of 8x8, and the remaining kernel size are 3x3. The batch normalization layer separates them. RELU activation function is used in convolutional layers. Batch normalization is used for accelerating convergence. A dropout layer is placed on the sixth layer of RELU to prevent overfitting. The model is trained using the triplet loss function. Feature-based matching consists of two parts which are feature detection and matching. SIFT feature points are chosen to get local feature points because SIFT Features are intolerant to variation in Rotation scale or brightness. For achieving feature point description, a deep convolutional neural network model is used. The image patch gives us input to the trained model and obtained 128-dimensional feature descriptions, representing the description of the image feature points. The information obtained from the feature description is used to build KD-tree. KD-tree is used to find corresponding feature points. Finally, from comparison results with other methods shows the proposed method is intolerant to geometry, illumination, and appearance.

2.8. Speech recognition

Speech recognition is very troublesome under noisy environments, and visual speech recognition can improve the quality of speech recognition technologies. Observing and understanding lips, eyebrows, and face movement can pave the way to recognizing the words. Mudaliar et al., (2020) proposed a deep learning approach for visual speech recognition [24]. Figure 7 depicts the operational framework of speech recognition. The model consists of 3D convolutional layers of ResNet architecture as encoders and Gated Recurrent Unit (GRU) for decoding. Input is a video signal, so the Resnet input layer is modified by adding a 3D convolutional layer, and the remaining layers are kept as 2D convolutional layers. This part is the encoding part, where the features from the video are extracted. The Gated Recurrent Unit decodes the features, and each frame is extracted from video to find the ROI or the region of the lip using OpenCV, then the frames containing the ROI are added to an array. This array becomes the input to the model. The encoder and decoder were trained separately and gave a training accuracy of 99% and validation accuracy of 90%. The model performance on frames with facial hair features is not good, but this limitation can be eliminated by modifying the dataset.

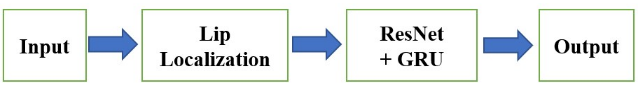

Fig. 7. Block diagram of speech recognition system

3. Conclusions

Applications of deep learning methods are growing to wider fields of human problems [25-29]. CNN and RNN are widely popular and have been used in most of the recent deep learning applications. Automatic feature extraction from input data by different CNN models has given many advantages for developing artificial intelligence. Many pre-trained CNN architectures are available, so these networks are fine-tuned in the particular dataset for each of the specific uses. CNN can understand the pattern in spatial and pixel information present in images, so these are widely used in image and video datasets. The recurrent-based neural network helps to understand the pattern in time-varying data such as audio signals. Recurrent neural networks having a recurrent weight that helps retain previous information in the network give a memory effect. Due to the vanishing gradient problem, LSTM and GRUs are considered for long sequences. Gates's presence in them enables them to learn information selectively. Recurrent networks are used for de-noising of signals which outperform traditional methods. The major limitation of deep learning supervised methods is the lack of sufficient labeled data. Many of the literature have used custom-made datasets by manually labeling them.

Each real-life application dataset has distinct properties, regardless of this, deep learning performance is more accurate. Besides of designing a new algorithm, some changes in the steps of deep learning may result in the improved performance. Selection of optimal parameters is also a major concern for deep learning. Time and space complexity are also major issues, while using the deep learning approach. Properly selecting the hierarchy of layers and supervising the learning process are most significant components in developing a successful deep learning model. However, the improved performance of deep learning can bear this limitation.

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