Educational Administration: Theory and Practice
2023, 29(1) 555 - 562
ISSN: 2148-2403
https://kuey.net/

Review Article

Deep Learning In Visual Speech Recognition: A Review Of Recent Developments And Performance Analysis

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Citation: Mr. Aditya Nivas Magdum *et al*, (2023) Deep Learning In Visual Speech Recognition: A Review Of Recent Developments And Performance Analysis, *Educational Administration: Theory and Practice*, *29(1)* 555 - 562
Doi: 10.53555/kuey.v29i1.7847

ARTICLE INFO

ABSTRACT

Visual Speech Recognition (VSR) is especially important in situations where acoustic signals are distorted, for example, in noisy environments or for people with hearing loss. This review aims at identifying the critical difficulty that arises from the visually similar phonemes or visemes which greatly affect the VSR. Visemes are other phonemes that are visually similar and hence pose a challenge when distinguishing them. We discuss the phoneme-viseme mapping and the effects of these similarities on VSR in low acoustic conditions. Different ways of improving VSR accuracy are described, such as data-oriented methods based on machine learning and deep learning algorithms, integration of vision with other sensory inputs, and context-based recognition systems that use linguistic context. We also discuss the existing methods of VSR systems including LipNet and LipReading in the Wild (LRW) and their drawbacks in practical scenarios. Future directions are concerned with the possibility of using both visual and degraded acoustic signals, new NN structures, individual VSR systems, and enhancements of real-time signal processing. The purpose of this review is to give a clear picture of the existing literature on the difficulties and possibilities of improving VSR accuracy in a low acoustic environment so that better communication technologies can be developed.

Keywords: Visual Speech Recognition (VSR), Visemes, Low Acoustic Environment, Machine Learning, Multimodal Fusion.

Introduction

In the field of speech recognition technology, Visual Speech Recognition (VSR) has attracted much attention because it can work in situations where acoustic-based systems are problematic. Such environments include those with high background noise, low signal quality, or no sound at all – conditions where conventional speech recognition systems perform poorly or are completely unreliable (Potamianos, Neti, and Luettin, 2004). VSR also has a major role in assisting those with hearing impairment by enabling their chance to use lip reading or the visual bluff of the face (Zhou et al., 2021).

One of the main challenges of VSR systems is the uncertainty of visual signals especially in differentiating between visually similar phonemes (visemes). Visemes are subsets of phonemes where they may be acoustically distinct, but they look similar because they require lip and mouth postures to create the sounds. For instance, the bilabial phonemes /p/, /b/, and /m/ have similar lip-closure when produced and are therefore in the same group of visemes (Bear et al., 2017). This is a big issue with VSR systems because there are times when these phonemes look very different, and one cannot differentiate them with vision alone. The consequence of this is an increase in recognition errors and a decrease in the overall accuracy of the system particularly in a low acoustic environment where audio input is either low or unavailable at all (Chung, Senior, & Vinyals, 2016).

Significance of Visual Speech Recognition

VSR is essential in various applications, such as:

- Assisting the hearing-impaired: VSR systems help in speech-to-text conversion for the hearing impaired to reduce the extent to which they rely on acoustic media for passing information.

- Human-computer interaction: Due to complications brought about by noise or the need for silence (for instance hospitals or libraries), VSR systems enable interaction with machines or gadgets by way of silent speech interfaces (Duan et al., 2020).
- Surveillance and forensics: The VSR-based lip-reading technologies can be used to synthesize speech from the video where audio is missing or of low quality.

Since VSR systems are incorporated into various technologies, the differentiation of visually similar phonemes is essential for the effectiveness of the system and its application. This problem is even more evident in low acoustic conditions where there is a high dependence on visual information since there are either low or no acoustic signals.

Visually Similar Phonemes and Their Impact on VSR

The main issue in VSR is that the movements of the human face during speech are not always unambiguous and can include more than one phoneme. Some phonemes are similar in terms of used movements; if two phonemes are similar, they are highly overlapping for the visual modality and vice versa for the auditorial modality, for instance, bilabial and labiodental phonemes are quite similar. Plosive phonemes for instance /p/, /b/, and /m/ involve a closure of the lips and the subsequent release of the closure with a burst of air or a stream of airflow which is grossly invisible. This is further extended if labiodental phonemes which involve pressing of the lower lip to the upper teeth for example /f/ and /v/ are taken into consideration.

If the acoustic signature of these sounds is not available, VSR systems are unable to resolve such ambiguities and hence the misclassification rates rise. This is known as the viseme ambiguity problem and creates a significantly high barrier to attaining high levels of accuracy in realistic VSR applications, especially in low acoustic or silent environments (Chung & Zisserman, 2017).

Review Objectives

The primary objectives of this review are as follows:

1. Analyze the Phoneme-Viseme Relationship: To further investigate how various phonemes are clustered into visually similar viseme categories and the difficulties they present to VSR systems in low acoustic conditions.
2. Evaluate Current Approaches to Overcome Viseme Ambiguity: To review current approaches used in improving the accuracy of VSR, especially concentrating on techniques such as visual feature extraction, machine learning, and multimodal fusion.
3. Propose Future Directions for Enhancing VSR Systems: To propose possible future directions of VSR research, including contextual models, hybrid schemes, and individualized systems, that can eliminate the errors resulting from visually similar phonemes and enhance the stability of the systems in practical use.
4. Provide a Comparative Analysis: To use a set of reference VSR systems to demonstrate how different solutions perform in conditions with low acoustic input or noisy environment, and how they address the problem of visually similar phonemes.

By reviewing these areas, this paper will give an overview of the status of VSR technology and suggestions for further research and technology development to solve the problem of visually similar phonemes.

Phoneme-Viseme Relationship

Phonemes are the smallest units of the sound of any language and because of their acoustic parameters, it is possible to distinguish between word and meaning in spoken language. While phonemes the identification of these phonemes as they look like when written are called. The problem with VSR is that many of the phonemes that are acoustically different are visually very similar when spoken. This leads to a situation where one or several phonemes may appear to be virtually identical as far as the visual signal is concerned, a situation that makes it problematic for the VSR system to disentangle between them clearly (Bear et al., 2017).

Thus in spoken language, lips, teeth, and tongue make different movements as a way of producing other different phonemes. However, these movements are not always easily distinguishable enough for identification without the use of audio. This visual correlation is especially detrimental in VSR systems that only depend on the visual input, for instance, in low acoustic conditions where the acoustic signal is either weak or absent. For instance, bilabial sounds like /p/, /b/, and /m/ entail the closure of lips, and consequently, lips cannot help to distinguish between the three sounds (Barker et al., 2003).

Table 1. Common Examples of Visually Similar Phonemes Grouped into Visemes

Phoneme Group	Viseme	Example Sounds
Bilabial	/p/, /b/, /m/	"pat", "bat", "mat"
Labiodental	/f/, /v/	"fine", "vine"
Alveolar	/t/, /d/, /n/	"top", "dog", "not"
Velar	/k/, /g/	"cat", "go"

Dental	/θ/, /ð/	"thin", "that"

Table 1 also illustrates that, for example, several phonemes are grouped into one viseme because of the similarity of their articulatory movements. For instance, bilabial phonemes (/p/, /b/, and /m/) are produced by the approximation of the lips and because of that, they cannot be distinguished. This is a major problem for VSR systems because, although the sounds are phonetically different, the lip movements that generate them are identical.

Bilabial Phonemes (/p/, /b/, /m/)

Bilabial type of phonemes is those in which the lips are blocked and then dropped or in which the breath is released or there is a puff of breath within the nostrils. /p/ and /b/ are voiced and have an explosive burst of air out of the mouth, /m/ is voiced, and the air is expelled through the nasal cavity (Barker, Ma, & Cox, 2003). However, since all three phonemes, require the same initial lip movement the three phonemes are grouped under the one viseme. This makes it hard for VSR systems to go between “pat,” “bat,” and “mat” without other information as the visual data are lacking.

Labiodental Phonemes (/f/, /v/)

Labiodental phonemes are made by approximating the lower lip to the upper teeth and passing air through the resulting narrow channel. This articulation leads to an almost identical visual configuration for /f/ and /v/. The only major distinction is differentiated by the difference in voicing: /f/ is voiceless while /v/ is voiced (Potamianos, Neti, & Luettin, 2004). However, VSR systems that depend only on the visual input cannot detect voicing and therefore cannot distinguish between ‘fine’ and ‘vine’ based on lip movements.

Alveolar Phonemes (/t/, /d/, /n/)

Alveolar phonemes are those for which the tongue contacts the alveolar crest or approximates it, which lies just behind the last crown of teeth. Even though/t/, /d/, and /n/ are acoustically distinctive in the sense that /t/ is voiceless, /d/ is voiced, and /n/ is nasal, the non-acoustic characteristics of the articulation are similar, and the contact point of the tongue with the ridge (Chung & Zisserman 2017). This feature of how the words are delivered to VSR systems makes the systems to struggle distinguish between “top,” “dog,” and “not” unless the system receives additional information or an audio cue.

Velar Phonemes (/k/, /g/)

Velar phonemes therefore require the back part of the tongue to come into contact with that part of the mouth known as the velum. Speaking of voicing, /k/ is without vocal cords vibration while /g/ is with vibration (Bear et al., 2017). Although they are articulated in the back of the mouth, the information visible to a VSR system is limited because most of the movement is concealed. The lack of such specification puts more emphasis on other signals, including contextual proration or multimodal signals, to differentiate between “cat” and “go.”

Dental Phonemes (/θ/, /ð/)

Dental phonemes are produced by having the tongue against the upper teeth. The only contrast between /θ/ that is represented by the phoneme ‘thin’ and /ð/ as in ‘that is that’ is that one is voiceless while the other is voiced (Potamianos et al., 2004). As with other phoneme pairs, their visual depiction is very similar since the position of the tongue and teeth is similar. This becomes a problem when trying to distinguish between these sounds simply by examining the pictures of the objects that create these sounds.

Difficulties of Viseme Ambiguity in VSR Systems

The division of phonemes into visemes poses several difficulties for the VSR systems. Since VSR systems depend on the extraction of visual features to map visemes to phonemes, misclassifications are common due to the ambiguity of visemes in a group. The absence of acoustic information worsens the problem, particularly in low acoustic conditions where the system must rely on visual data almost exclusively (Zhou et al., 2021). The problem has been addressed by attempts at using multimodal fusion techniques that involve the use of visual, auditory, and even contextual information. However, one of the main challenges in the field is the ability to differentiate between similar visemes accurately.

Solutions and Future Directions

To address these issues, researchers have proposed several approaches, including enhancing the techniques for extracting visual features, incorporating contextual information, and training models to address the visual ambiguity problem. Studies that combine audio, video, and contextual data have been found to improve the performance of VSR systems. These methods make use of the fact that different data sources are generally more complementary to each other in recognition performance, particularly in difficult conditions (Chung et al., 2016).

Impact of Visually Similar Phonemes on VSR Accuracy

The problem of visemes, which are visually like phonemes, is one of the key concerns of Visual Speech Recognition (VSR). As mentioned earlier, visemes are the visual equivalent of phonemes; however, because of the constraints of the human vocal tract, several phonemes are realized with the same viseme. This issue poses a major challenge to enhancing the precision and speed of VSR systems, especially in situations where audio cues are attenuated or non-existent (Bear, Harvey, & Theobald, 2017).

Effect of Viseme Ambiguity on VSR Efficiency

The presence of multiple phonemes by a single viseme confuses the visual speech recognition systems. When visual data is the main or the sole input, this vagueness leads to higher error rates and lower recognition performance. However, they fail to differentiate between phonemes that are articulated similarly in the visual modality, for instance, /p/, /b/, and /m/ (Zhou et al., 2021).

- **Higher Error Levels in VSR Systems**

The problem of visually similar phonemes is one of the main sources of errors in VSR systems because the phonemes are often confused with each other. Bear et al., (2017) have established that for VSR systems that work in low acoustic environments where audio data is either scarce or completely missing, the error rates shoot up by as much as 50% because of viseme ambiguity. This is because, when there is no audio input, the system will only have to rely on visual features, which are usually not enough to differentiate between some phonemes.

Furthermore, the problem of mapping one or many phonemes to a viseme causes misclassification of the words, especially in real-time speech recognition, in which the system must analyze the visual data instantly. In such cases, contextual information and temporal dependencies are often insufficient to resolve ambiguities promptly (Chung & Zisserman, 2017).

- **Lowered Total Identification Rate**

In low acoustic input conditions like noisy environments or for hearing-impaired users, the use of visual information is very important. However, the problem of viseme overlap greatly reduces the accuracy of the VSR systems. Although new systems that use deep learning and neural networks have enhanced the VSR precision, these systems lack precision when confronted with the uncertainty of visually similar phonemes (Assael et al., 2016).

The fact that some visemes are almost indistinguishable from each other also lowers the recognition rate, particularly in real-life conditions. For example, in cases where the background noise interferes with the audio signal, in crowded places or industrial areas, VSR systems rely more on lip movements. If the system is exposed to two words that are phonemically similar but belong to different viseme groups, for instance, “bat” and “pat”, then the system will make classification errors (Bear et al., 2017).

- **Real-time processing has been known to present several challenges.**

The real-time processing of VSR systems is usually compromised by the necessity to disambiguate visemes in the same manner in real-time. Specifically, noise or conditions with little acoustic signal make this difficult. For instance, in telecommunication for the hearing impaired, VSR systems have to analyze visual information as fast as possible to facilitate communication. However, since there are viseme groups, this process is less efficient and takes more time than other approaches to speech recognition (Potamianos, Neti, & Luettin, 2004).

Possible Remedies for Viseme Ambiguity

Solving the problem of viseme ambiguity in VSR systems means creating new methods of its solution, which are more complex than the lip-reading methods. Several potential solutions have been proposed to mitigate the effects of visually similar phonemes on recognition accuracy:

1. **Multimodal Data Integration:** It is also suggested that by integrating audio, visual, and contextual information, VSR systems can differentiate between visually similar phonemes. The results of the experiments have revealed that the multimodal systems that combine the acoustic signals with the visual input can enhance the recognition accuracy by providing additional hints to remove the uncertainty (Zhou et al., 2021).
2. **Contextual Analysis**: Other factors like the syntactic structure of the sentence, the frequency of the words, and their semantic context can assist VSR systems in minimizing the effects of viseme ambiguity. For example, when the system is in doubt as to whether the word is ‘bat’ or ‘pat’, the contextual analysis can help in choosing the most probable word based on the other words in the sentence (Chung et al., 2016).
3. **Machine Learning Models:** Recent studies in deep learning and neural networks have helped enhance the VSR systems’ performance in disambiguating visemes. CNNs and RNNs have been applied for feature extraction from visual data and modeling temporal dependencies to enable the systems to differentiate between visually similar phonemes (Assael et al., 2016).
4. **Temporal Smoothing:** Temporal smoothing techniques allow VSR systems to track sequential movements of the lips and other articulators, which give more context to distinguish phonemes. For instance, the movement patterns of /p/ and /b/ may be almost identical, but temporal analysis of lip movements can reveal differences in the onset and offset that are not discernible through spatial analysis alone (Potamianos et al., 2004).

The effect of visually similar phonemes on VSR accuracy is a significant problem that needs to be solved to increase the efficiency of speech recognition systems in low acoustic conditions. The viseme-phoneme mapping results in high error rates and low accuracy in VSR systems especially when implemented in real-time environments with noise. Nevertheless, there are problems with integrating multiple modalities, contextual analysis, and machine learning that provide solutions to this problem. These approaches are expected to remain relevant as technology advances to improve the reliability and effectiveness of VSR systems.

Approaches to Enhance VSR Accuracy in Low Acoustic Environments

Enhancing VSR performance in low acoustic conditions is a complex problem that has various aspects. Different methods such as data based methods, fusion of different modalities and contextual based recognition systems have been identified as useful in improving the performance of VSR. All of these approaches deal with the issues connected with visually similar phonemes, using sophisticated computational methods and models to increase the recognition rate.

Data-Driven Approaches: Machine learning and deep learning

Several improvements have been made on the kind of machine learning, including the CNNs as well as the RNNs, making VSR systems more efficient in the current past. These models can capture small movements of the lips which are crucial in discriminating between similar phonemes.

Table 2. Overview of Data-Driven Approaches for Enhancing VSR Accuracy

Method	Description
CNNs	CNNs are designed to automatically extract visual features from sequences of lip images. By employing multiple layers of convolutional filters, CNNs can capture local patterns in the data, effectively enhancing the recognition of minute differences in lip shapes and movements that are often indicative of different phonemes (LeCun et al., 2015).
RNNs (LSTM networks)	Long Short-Term Memory (LSTM) networks, a type of RNN, are particularly suited for analyzing temporal data such as lip movements over time. LSTMs can maintain long-term dependencies, allowing them to consider the sequence of lip movements in conjunction with the temporal context, thus improving the ability to differentiate phonemes that might look similar at a given moment (Hochreiter & Schmidhuber, 1997).

The use of these approaches has brought about improved VSR accuracy due to implementation of the approaches. For example, models employing CNNs and LSTMs has caused the error rate to decrease by 30% and this has been useful in challenging situations that do not allow voice input (Assael et al., 2016).

Multimodal Fusion Techniques

Other information that can be fused may include facial expressions, gestures, head movements, and among others; aside from the visual information for enhance the rate of speech recognition. As multiple sources of information are integrated, VSR systems are able to resolve the ambiguities resulting from visually similar phonemes.

Table 3. Comparison of Multimodal Fusion Techniques

Fusion Method	Description
Early Fusion	This method combines visual data with other sensory inputs before analysis. By merging features at the input level, the system can leverage complementary information from various sources, improving its ability to identify the correct phoneme even when visual signals are ambiguous (Baltrusaitis et al., 2019).
Late Fusion	In this approach, different modalities are processed independently, and decisions are merged after the analysis phase. Late fusion allows for individual strengths of each modality to be highlighted, with the final decision making based on a combination of outputs, leading to a more robust recognition performance (Kwon et al., 2020).

Multimodal fusion can be valuable to enhance the weak VSR ability especially when the background is distorted or noisy thus it could be difficult to obtain a clear visual input that could be used for the recognition process (Zhou et al., 2021). Studies show that multimodal VSR systems can attain recognition rates of more than 85% in conditions that were previously infeasible for unimodal systems (Potamianos et al., 2004).

Contextual Based Recognition Systems

Contextual recognition systems define the words and phonemes of the context and then apply the same to deduce the most probable phoneme when faced with similar visual symbols. This approach employs language models and probabilistic framework such as Hidden Markov Models (HMM) to enhance the VSR in real-time.

Table 4. Types of Contextual-Based Recognition Models

Model Type	Description
N-gram Models	N-gram models predict phoneme sequences based on the probability of occurrence of previous words. By considering the context of neighboring phonemes, these models can significantly reduce ambiguity in cases of viseme overlap, enabling the system to infer the most likely phoneme based on context (Manning & Schütze, 2000).
Bayesian Networks	Bayesian networks provide probabilistic estimates for phoneme selection, incorporating prior knowledge and contextual information. This allows the system to make informed decisions about phoneme recognition, significantly enhancing VSR accuracy, particularly in low acoustic environments (Koller & Friedman, 2009).

Contextual based recognition systems have shown significant improvement in recognition accuracy some of which are as follows: Chung et al. (2016) showed more than 20% improvement in recognition accuracy in difficult environment where visually similar phonemes are likely to occur.

The Current State of VSR Systems

Current VSR technologies have been advanced regardless of significant problems in the difficulty of distinguishing between visually similar phonemes in real conditions. Systems like LipNet and LipReading in the Wild (LRW) have shown good performance measures in controlled scenarios but fail to perform as well in noisy or low acoustic environments which are more realistic.

LipNet

LipNet is one among the latest developments in VSR that uses deep learning techniques to accomplish lip-motion based speech recognition. LipNet was introduced by Assael et al. (2016) and it is a system that uses CNNs and RNNs to learn about sequences of lip images hence making it learn temporal structure of the visual data. The system was trained on a set of 5000 video clips with the possibility to learn subtle differences in lip movements corresponding to distinct phonemes. This training approach has resulted in reported recognition accuracy of 93.4% in controlled environment, which is quite impressive compared to previous models (Assael et al., 2016).

Nevertheless, as has been noted, an application of LipNet results in low performance in more complicated situations, although its effectiveness is 92% in simple conditions. Animation or complex backgrounds, and when the audio is full of noise or when there are other objects in the video, for instance in, the model can have difficulties in distinguishing between similar phones, for instance, /p/ and /b/. These phonemes, although acoustically different, may sound quite alike when emitted, thus receiving poorer performance in terms of error when used for practical purposes (Zhou et al., 2021). Therefore, LipNet produces good results in the best conditions, however, in a case when the quality of the visual input declines due to specific factors, the efficiency is significantly lower.

LipReading in the Wild (LRW)

Likewise, the LRW dataset is centered on large vocabulary recognition from visual input only. The LRW project is an attempt to improve VSR using a larger vocabulary and a wider range of speech patterns, with the use of videos that contain people speaking several words in real life situations (Chung & Zisserman, 2016). Therefore, by training the acoustic-phonetic mapping on many lip movements for various phonemes, LRW should aid the system in visually perceiving speech more effectively.

Nonetheless, LRW approach also has difficulties like LipNet when the accuracy of the vision recognition is largely enhanced. For instance, the system's performance may be greatly affected by interference from other sounds or when the subject's face is partially occluded. The studies show that even the most successful models can have the recognition accuracies of only 50% in the conditions of high VN (Potamianos et al., 2004). This underscores the need for more enhancement of VSR technologies, especially in environmental changes.

In general, the status of VSR systems shows that the task of achieving high accuracy in practical applications is challenging. Thus, LipNet and LRW form a basis for future enhancements in VSR; nonetheless they do expose the current artifacts of the model to distinguish between adjacent phonemes which are often difficult to differentiate in noisy or unpredictable circumstances. Future work should therefore focus on enhancing the stability of these models; either by using more elaborate data augmentation techniques, or by fusing the different modalities and using better contextual analysis mechanisms.

Future Directions

Some of the promising directions that may further advance the development of VSR as a field are the following: Several of them can dramatically improve the effectiveness of VSR systems, particularly, in the discrimination of the phonemes that are similar in visual appearance. The subsequent sections of this paper describe some of the most important directions for the further development of VSR technology.

Hybrid Models

The most significant opportunity for the development of more accurate VSR systems seems to be the use of combined models based on both visual and degraded acoustic information. This approach is designed to take advantage of the characteristics of visual information while minimizing the shortcomings associated with low acoustic environments. The literature review shows that multimodal systems can perform better than single-modality systems because they offer supplementary information (Zhou et al., 2021).

For example, when available, using lip movements as the visual input together with the acoustic signals can form a better recognition system. Among the strategies such as the late fusion where the results from the audio and visual recognition models, some of them could be implemented to enhance the final decision-making step as recommended by Wang et al., (2018). Also, the context information extracted from the acoustic signal can be used to help the model to disambiguate the visually similar phonemes. The combination of these approaches might help VSR systems to function better in real-world environments, where noise and other disturbances negatively affect acoustic signals.

Advanced Deep Learning Models

Future work in deep learning, especially with CNNs and RNNs, can be expected to improve SR, more specifically VSR. Further work should be devoted to the creation of models that would be able to track minor changes in lip movements, in conditions that are difficult to observe. New efficient approaches such as attention mechanisms, where the model is trained to focus on some parts of the input data that contribute to the recognition of visemes, can enhance the system's discriminative ability of similar visemes (Vaswani et al., 2017). In addition, there is an opportunity to create GANs for data augmentation, which will create training data that will resemble different environmental conditions and lip movements. This would help to increase the stability of the model and diversify the exposure to various conditions during training, therefore improving the model's performance in practice applications (Gulrajani et al., 2017).

Personalized VSR Systems

Two important directions for future studies have been identified, including the design of VSR systems specific to a person's speech and lip movements. Such systems could use user-specific information to adjust the recognition process to the user's articulation, lip contour, and speaking patterns. Personalization could improve accuracy by helping the system to concentrate on the viseme configurations relevant to the particular speaker (Wang et al., 2020).

The use of user feedback loops in VSR systems would complement the learning process from system performance to improve recognition continually thus improving the performance of the system in the future. Some of the personalization strategies can also be beneficial for the applications for speech-impaired people or those who have a heavy accent; such users have different visual speech, which is often not detected by the models.

Real-Time Processing

Finally, it is essential to increase the speed of computation to achieve real-time VSR for practical applications of this technology. The current models are computationally intensive and therefore not suitable for real-time applications such as speech recognition for the hearing impaired (Yu et al., 2021).

More studies could be made on how to enhance the models that are undergoing so that the sizes of neural networks could be reduced by employing strategies such as model simplification and model to a fixed point. Moreover, exploring edges related to new models that suggest data processing occurs locally to minimize response time and rely more on the device (Zhang et al., 2020).

Conclusion

The study of visually similar phonemes is a major concern in the VSR, especially in low acoustic conditions. As the technology of VSR develops, the knowledge of phoneme-viseme relation is vital for improving the efficiency and effectiveness of the tool. In this review, the author of the paper has described the impact of the availability of the phonemes that are visually very much like that of the VSR performance and expressed that due to the presence of these viseme groups, errors are more likely to take place and real-time processing capability of the VSR is not quite effective.

New approaches to improving the accuracy of VSR rely primarily on data-driven techniques such as machine learning and deep learning algorithms that demonstrate high capability to differentiate small movements in the lip area. In addition, the attempts to employ multimodal fusion, contextual recognition, and personal VSR systems will help to enhance the VSR systems' effectiveness in the practical context.

In the future, better methods to differentiate between visually similar phonemes will be possible using both visual and degraded acoustic signals, and better architectures for deep learning and real-time processing. These systems' development makes it possible for those who work or live in noisy regions or suffer from hearing impairments in the current speech recognition technology to have a shot at enhanced communication.

In conclusion, it is possible to ascertain that for the present VSR is among the continuously advancing technologies and much more investigation must be carried out to enhance the reliability of the method and expand the spectrum of its usage. Understanding the challenges of visually similar phonemes and opening for new solutions, the future of VSR can enhance the communication experiences for all users, and thus, close the gap between the auditory and visual channels in speech recognition.

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