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"What CNN Neural Networks Can Do For Education and How They Could Change the Field"

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Abstract

"This paper provides a comprehensive analysis of CNN's (Convolutional Neural Network) potential in the classroom and its implications for the future of education. The purpose of this research is to investigate how CNNs may be used in the classroom, specifically for tasks like deep learning ; speech and picture recognition, NLP, and more. Improved student engagement, individualised instruction, and higher achievement are just some of the many acknowledged benefits of incorporating CNNs into the classroom. This paper also emphasises the importance of recent developments in educational technology and the need to use CNNs in the classroom.

Finally, the paper discusses the potential benefits and obstacles to incorporating CNNs into classroom instruction. Our goal in doing this extensive study is to shed light on the strengths and potential of CNNs in the classroom and show how they may be used to benefit students' education."

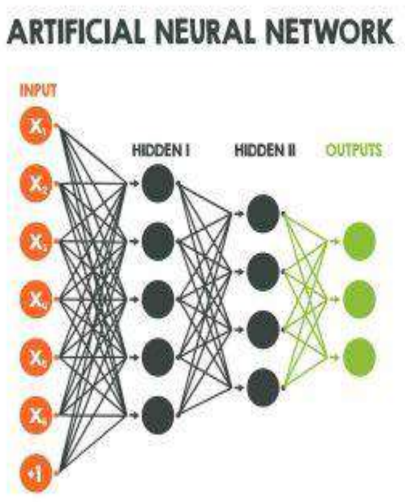
Keywords: CNN's (Convolutional Neural Network) , Educational technology, Deep learning Higher Achievement.

1. INTRODUCTION

Deep Learning

Using complicated algorithms and artificial neural networks, Deep Learning has emerged as a powerful tool for processing massive data. This method teaches computers to learn from their mistakes, classify information, and recognise images in the same ways that a human brain does. Convolutional Neural Networks (CNNs) are a popular form of artificial neural network in the field of Deep Learning, typically employed for the purposes of image/object recognition and classification. So, Deep Learning uses a convolutional neural network (CNN) to spot objects in photos. Convolutional neural networks (CNNs) are increasingly important in a wide variety of fields, from computer vision (such as localization and segmentation) and image processing to natural language processing (NLP) and video analysis (to spot obstacles in self-driving cars). Because of its usefulness in these newly developing fields, CNNs have become increasingly prominent in the field of Deep Learning.

Brain's Architecture Inspired CNNs



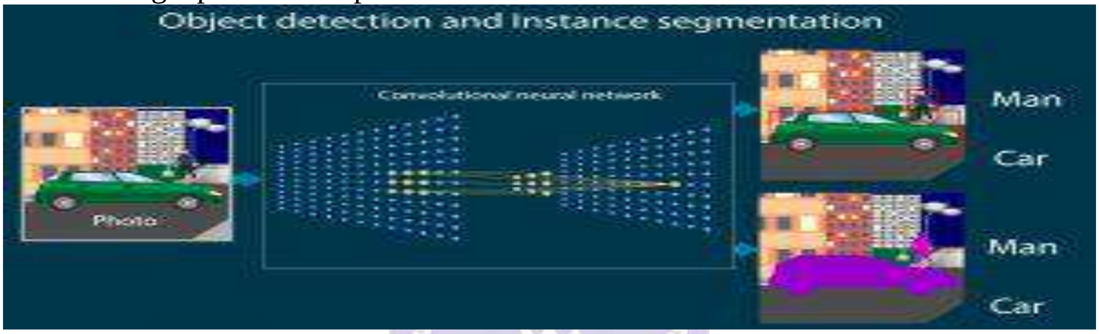
There are input layers, hidden layers, and output layers in a typical neural network. The structure of the brain serves as a model for CNNs. Artificial neurons, also known as nodes, in CNNs receive data as input, process it, and then transmit the results as output, just like real neurons in the brain do. The picture is used as input. The image's pixel values are read in as arrays by the input layer. Multiple hidden layers are possible in CNNs, each of which calculates and extracts features from the image. Convolution, pooling, rectified linear units, and fully connected layers are all possibilities here. In order to begin extracting features from an input image, the first layer, called convolution, must be used. When an object is sent through the fully linked layer, it is immediately identified and placed into the appropriate output category.

Convolutional neural networks are feed forward networks because data flows only from their inputs to their outputs. Similar to ANNs, CNNs take their inspiration from the workings of the human body. Their structure is inspired by the brain's visual cortex, which has alternating layers of simple and complex cells. There are many different CNN architectures, but they all share the modules of convolutional and pooling (or subsampling) layers. According to "Deep Convolutional Neural Networks for Image Classification: A Comprehensive Review," published in the MIT Press journal "Neural Computation," "either one or more fully connected layers, as in a standard feedforward neural network," follows these modules.

A Powerful Deep Learning Resource

Since CNNs can recognise patterns in images, they have drastically altered how we approach image identification. Since their results are so precise, they are the go-to architecture for image classification, retrieval, and detection applications.

Because of their excellent quality results and their ability to precisely pinpoint where in a picture a person, car, bird, etc. is located, these methods find widespread use in practical testing environments. Because of this, they have become the standard procedure for making predictions using a picture as input.



- Essential to the success of CNNs is their "spatial invariance," or the capacity to learn to recognise and extract visual features regardless of their location within the image. The requirement for manual extraction is eliminated because CNNs can automatically learn features from the image/data and extract the desired information. As a result, CNNs are a powerful resource for achieving precision in Deep Learning.
- 'Neural Computation' states that "the goal of the pooling layers is to minimise the spatial resolution of the feature maps and so achieve spatial invariance to input distortions and translations." In addition to lowering memory and computational costs, the pooling layer also makes processing the image faster by reducing the number of parameters that must be adjusted.
- CNNs can be used for a variety of data analysis and classification challenges; however, image analysis has been where they have seen the most success to date. Therefore, they can be used in a wide variety of fields to achieve accurate results, including but not limited to: face identification; video classification; street/traffic sign recognition; galaxy classification; interpretation and diagnosis/analysis of medical images; and so on.

II. CNN'S (CONVOLUTIONAL NEURAL NETWORK) POTENTIAL AND BENEFITS IN THE CLASSROOM

Convolutional Neural Networks (CNNs) have the potential to be a useful tool in the classroom for image and video analysis tasks. They can be used for tasks such as object recognition, image classification, and video analysis. For example, CNNs can be used to automatically grade multiple-choice tests by analyzing images of the filled-out test sheets. CNNs can also be used to analyze video footage to detect and track specific objects or actions. In addition to these specific uses, CNNs can also be used as a teaching tool to help students understand the inner workings of deep learning models. By training and experimenting with CNNs, students can gain a better understanding of how these models work and how they can be applied to different tasks. CNNs can also be used to improve accessibility in the classroom. For example, CNNs can be used to automatically caption images and videos, making them more accessible for students with visual impairments.

Overall, CNNs have the potential to be a valuable tool in the classroom for both teachers and students. However, it is important to note that the use of CNNs in the classroom should be carefully considered and implemented in a way that is appropriate for the specific task and classroom setting.

III. CNN IMPLICATIONS FOR THE FUTURE OF EDUCATION

Image and Video Analysis: CNNs can be used to analyze images and videos for various purposes, such as object recognition, image classification, and video analysis. This can be useful for tasks such as automatically grading multiple-choice tests or tracking specific objects or actions in a video.

Teaching Tool: CNNs can be used as a teaching tool to help students understand the inner workings of deep learning models. By training and experimenting with CNNs, students can gain a better understanding of how these models work and how they can be applied to different tasks.

Improved Accessibility: CNNs can be used to improve accessibility in the classroom by automatically captioning images and videos, making them more accessible for students with visual impairments.

Personalized Learning: CNNs can be used to create personalized learning experiences for students. For example, by analyzing a student's performance on a task, a CNN can suggest personalized learning activities or adjust the difficulty level of a task to match the student's abilities.

Real-time Learning: CNNs can be used to provide real-time feedback to students during a task. For example, a CNN can be used to analyze a student's handwriting or speech, providing instant feedback and suggestions for improvement.

Automation of Grading: CNNs can be used to automate the process of grading assignments and exams, reducing the workload for teachers and providing more accurate and consistent grading.

Predictive Analysis: CNNs can be used to analyze data on student performance and behavior, providing insights into areas where students may need additional support or intervention.

Automation of Administrative Tasks: CNNs can be used to automate administrative tasks such as attendance tracking and scheduling.

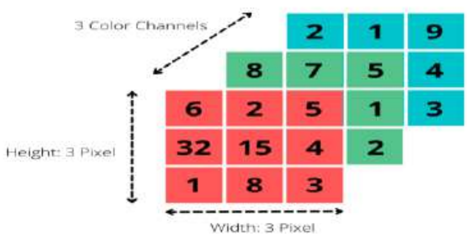
Overall, CNNs have the potential to greatly enhance the educational experience by providing new tools for analyzing and understanding data, personalizing learning, and automating administrative tasks. However, it is important to note that the use of CNNs in education should be carefully considered and implemented in a way that is appropriate for the specific task and educational setting.

IV. USEIN THE CLASSROOM, SPECIFICALLY FOR TASKS LIKE SPEECH AND PICTURE RECOGNITION, AND NLP

CNNs, or convolutional neural networks, can be used in the classroom for a variety of tasks related to deep learning, speech and picture recognition, and natural language processing (NLP).

PICTURE RECOGNITION

One way CNNs can be used in the classroom is through image and video analysis. For example, a CNN can be trained to recognize objects or actions in images and videos, which can be used in educational activities such as identifying different types of animals or analyzing historical events.



3x3x3 RGB Picture

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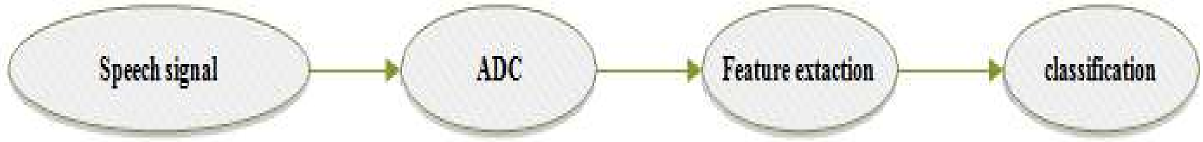
Additionally, CNNs can also be used for facial recognition, which can be used for attendance tracking or identifying students in need of extra support. Computers interpret an RGB image as the product of three separate matrices. It specifies the colour displayed by each pixel in the image. To accomplish this, we first define the red component in the first matrix, then the green component in the second, and finally the blue component in the third. Therefore, there are three distinct 3x3 matrices for a 3x3 pixel image.
Inputing each pixel into the network is how an image is processed. As a result, we need to supply 2002003=120,000 input neurons for a 2002003 image (i.e., 200200 pixels in size with 3 colour channels, such as red, green, and blue). So, there are 200 rows and 200 columns (or 200 * 200) in each matrix. This matrix is then present thrice, once for each of the primary colours (red, blue, and green). Since each neuron in the first hidden layer would have 120,000 weights from the input layer, this creates a problem. Because of this, as the number of Hidden Layer neurons is increased, the corresponding increase in the number of parameters is also expected to be rapid.
When we want to process larger images with more pixels and more colour channels, this difficulty increases. Overfitting is a likely problem for a network with so many parameters. This means the model will perform well when predicting data from the training set, but will struggle when applied to data it has not seen before. In addition, the network is likely to stop paying attention to specifics in the images as they get lost among the many parameters. On the other hand, such minute features as a dog's nose or ears can be the deciding factor in a successful image classification.
Convolutional Neural Network
That's why the Convolutional Neural Network uses an alternative strategy, modelling human visual perception. To better understand a scene, our brains automatically break it down into numerous smaller sub-images. We process and interpret the image by piecing together these smaller images. How can a Convolutional Neural Network take advantage of this idea?
In the so-called convolution layer, the action takes place. To achieve this, we define a filter to specify the size of the partial images being examined, as well as a step length to specify the distance, in pixels, between each calculation. The image's dimensionality has been drastically lowered as a result of this change. After that, we reach the pooling layer. In terms of raw computation, this layer is identical to the convolution layer; however, we only retain the average or maximum value of the output. This helps keep crucial task-solving details that only exist in a handful of pixels.
At long last, we have a **fully-connected layer**, the kind of thing we're used to seeing in standard neural networks. We have successfully reduced the image size to where the tightly meshed layers can be used. Here we re-link the individual sub-images so that we can see the associations and perform the classification.
Now that we have a rough idea of what each layer does, we can examine the process of image classification in greater depth. In this case, we're looking to determine if a dog is present in a 4x4x3 image.
SPEECH RECOGNITION
Another way CNNs can be used in the classroom is through speech recognition. For example, a CNN can be trained to transcribe spoken words into text, which can be used to improve accessibility for students with hearing impairments or to analyze student speech for language development.


The general path to completion of speech recognition.

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ADC (analogue to digital converter) (spectral shaping) picking the sound wave and converting it into a digital form, then preemphasis filtering, then feature extraction, is the general path toward completion of speech recognition theory. The features that have been extracted will be sent on to the classification phase. Parameter transformation is one such method, and it entails a separation and concatenation procedure to convert the features that have been extracted into parameters that describe the signal.

Parameter conversion in observation vectors for signals is a part of statistical modelling . Sound recognition is a crucial component of many modern security and access control systems . Sound travels in waves, each of which is characterised by the rapid, high-frequency oscillation of higher-frequency tones. A microphone is an electronic device that "hears" sound and "sees" electrical current. The amplitude of a signal, represented by the shape of the wave, provides a rough idea of the amount of energy present. The FFT analyses the frequency components that make up a sound wave and highlights them with a diagram called a spectrum diagram because of the sound wave's inherent variability in frequency while still being closely spaced. . Voices travel through the air as sinusoidal waves.

Compared to lower pitches, higher ones vibrate at a higher frequency and thus more quickly. An audio signal is picked up from the airborne vibrations of a sound wave and transformed into electrical energy by a microphone. Noise levels are proportional to the amplitude of a speech signal. Our voices contain a wide range of frequencies, too. After summing up all of the individual frequencies, you get the final signal. The signal's breakdown into its component frequencies was used as a set of features for doing so.

The Fourier transform was used to break the signal up into its constituent parts. The Fast Fourier Transform (FFT) algorithm is commonly available for this purpose. By dividing the sound in this way, a spectrogram can be created. A spectrogram is created by segmenting a signal over multiple time periods. Then, the Fast Fourier Transform (FFT) is used to decompose the entire frame into its constituent frequencies. For each time period, an amplitude vector has been constructed. When time-aligned with the source audio signal, a spectrogram provides a visual representation of the constituent sounds . In regards to our work, we have compiled 30 people's thoughts from all over the world into 6 words. Individuals of varying ages and sexes have provided us with speech samples. The wide variation in word lengths that we recorded presented significant challenges. To accommodate these dissimilarities, various software packages have been developed (Audacity and Adobe Audition). A Convolutional Neural Network was used to identify and hone in on the most important aspects of speech (CNN). Since speech recognition is a multiclass classification process, the efficacy of CNN, the state-of-the-art deep learning method, has been studied. To find the best CNN structure that is able to solve our multiclass classification problem, we have tested and updated various types of CNN learnable parameters. The goal of applying a deep learning model is to locate the optimal model for our data conditions in order to finalise the process of control. There are numerous problems with the recording data, including those related to phonation, word placement during pronounciation, and the presence of background and recording device noises. Data have been collected under these conditions because our work is focused on controlling machine motion in real time via speech signal order.

NATURAL LANGUAGE PROCESSING

In addition, NLP is an important field where CNNs have been used extensively. This can be used in the classroom for tasks such as sentiment analysis, question answering, and text summarization. For instance, a CNN-based model can be trained to understand the context of a student's text and generate a summary of the main points, which can be helpful for students with reading difficulties.

Overall, CNNs can be a powerful tool for enhancing the learning experience in the classroom, by providing students with new opportunities to interact with and analyze digital content, and providing teachers with new methods to assess student performance and personalize instruction. However, it's important to consider the ethical and privacy implications of the technology and to ensure that teachers have the necessary training and resources to effectively incorporate CNNs into the classroom

V. RECENT DEVELOPMENTS IN EDUCATIONAL TECHNOLOGY RELATEDTO CNN

Recent developments in educational technology related to CNNs include the use of CNNs for:

Virtual Reality (VR) and Augmented Reality (AR) applications: CNNs can be used to analyze images and videos captured in VR and AR environments to detect student engagement and provide personalized feedback. This can be useful for tasks such as tracking student movements and interactions within a VR or AR environment, or analyzing student facial expressions to gauge engagement and understanding.

Automated Essay Grading: CNNs can be used to analyze written text, including essays, to provide automated feedback and grading. This can be particularly useful for tasks such as analyzing student writing for grammar, spelling, and punctuation errors, or analyzing student-written essays for content and organization.

Intelligent Tutoring Systems: CNNs can be used to analyze student interactions with an intelligent tutoring system, providing personalized feedback and guidance to students in real-time. This can be particularly useful for tasks such as analyzing student responses to questions, detecting patterns in student behavior, and providing targeted feedback and guidance to students.

Language Translation: CNNs are being used to improve machine translation of natural languages in educational settings, making it possible to provide subtitles or translations of educational videos, making it accessible to students who speak different languages.

Adaptive Learning: CNNs can be used to analyze student performance data and adapt the learning environment in real-time. This can be particularly useful for tasks such as adjusting the difficulty level of a task based on student performance, or providing targeted feedback and guidance to students based on their performance.

Student Engagement: CNNs can be used to analyze student engagement data, such as facial expressions, body language, and speech patterns, to provide real-time feedback to students and teachers about student engagement.

Recent developments in educational technology related to CNNs have focused on using these models to analyze visual data and student interactions, providing personalized feedback and guidance, and adapting the learning environment in real-time. However, it is important to note that these developments are still in the early stages and further research is needed to fully understand the potential benefits and limitations of using CNNs in education.

VI. OBSTACLES TO INCORPORATING CNNS INTO CLASSROOM INSTRUCTION

Data Privacy and Security: One of the main obstacles to incorporating CNNs into classroom instruction is the concern for data privacy and security. The use of CNNs in the classroom requires the collection of large amounts of data on students, such as images, videos, and performance data. This data must be protected to ensure that it is not misused or accessed by unauthorized parties.

Technical Expertise: Another obstacle to incorporating CNNs into classroom instruction is the need for technical expertise to set up and maintain the necessary infrastructure. This includes the need for specialized hardware and software, as well as the need for trained personnel to operate and maintain the systems.

Cost: The cost of implementing CNNs in the classroom can be a significant obstacle. The cost of purchasing or leasing the necessary hardware and software, as well as the cost of training personnel to operate and maintain the systems, can be prohibitive for many educational institutions.

Ethical and Legal Considerations: The use of CNNs in the classroom raises ethical and legal considerations, such as issues related to data privacy, security, and the use of automated decision-making systems. It is important to consider these issues and to ensure that the use of CNNs in the classroom is in compliance with relevant laws and regulations.

Lack of Understanding of CNNs: Another obstacle to incorporating CNNs into classroom instruction is the lack of understanding of these models among teachers, students, and other stakeholders. It is important to provide education and training on the use of CNNs in the classroom to ensure that they are used effectively and appropriately.

Lack of Resources: The lack of resources to train and support teachers in incorporating CNNs into classroom instruction is an obstacle. This includes the lack of resources to provide training on how to use CNNs, as well as the lack of resources to provide ongoing support and guidance to teachers as they integrate these models into their instruction.

Bias: CNNs are also prone to biases, which can be inadvertently incorporated into models if the training data is biased. This can lead to inaccurate or unfair results, which can be detrimental to the educational experience.

In conclusion, incorporating CNNs into classroom instruction is not without its challenges. Addressing these obstacles requires collaboration between educators, researchers, and policymakers, as well as an understanding of the technical, ethical, and legal considerations involved in using these models in the classroom. It's important to weigh the benefits and limitations of using CNNs in education and come up with a balance approach.

VII. CONCLUSION

In conclusion, CNN neural networks have the potential to greatly impact the field of education. They can be used for tasks such as image and video analysis, natural language processing, and facial recognition, which can enhance the learning experience for students and improve the efficiency of educational institutions. Additionally, CNNs can also be used for student assessment and personalized learning, by analyzing student performance data and providing tailored recommendations for improvement. However, it is important to note that the implementation of CNNs in education requires careful consideration of ethical and privacy issues, as well as the need for proper training and resources for educators. Further research is needed to fully explore the potential of CNNs in education and to develop effective strategies for their integration into the educational system.

VIII. REFERENCES

1. S. Hwang, “Recognition of teacher identity by special education classroom teachers,” *The Journal of Special Education*, vol. 35, no. 3, pp. 27–44, 2019.
2. M. G. Lindahl, A. Folkesson, and D. L. Zeidler, “Students’ recognition of educational demands in the context of a socioscientific issues curriculum,” *Journal of Research in Science Teaching*, vol. 56, no. 9, pp. 1155–1182, 2019.
3. W. B. Hansen, C. B. Fleming, and L. M. Scheier, “Self-reported engagement in a drug prevention program: individual and classroom effects on proximal and behavioral outcomes,” *Journal of Primary Prevention*, vol. 56, no. 2, pp. 456–462, 2019.
4. Y. Sekiguchi, “Activity systems analysis of classroom teaching and learning of mathematics: a case study of Japanese secondary schools,” *Educational Studies in Mathematics*, vol. 5, no. 2, 2021.
5. G. Zhao, W. Zhu, B. Hu, Q. Xia, S. Liu, and J. Chu, “Construction of intelligent analysis model of teaching behavior based on multi-dimensional feature fusion,” *E-education Research*, vol. 41, no. 10, pp. 36–44, 2020.
6. Y. Ya-jun, L Fei-fei, and C. Qiu, “Crowd behavior recognition algorithm based on combined features and deep learning,” *Computer Science*, vol. 46, no. 6, pp. l305–310, 2019.

7. A. M. Prado, R. Arce, and L. E. Lopez, "Simulations versus case studies: effectively teaching the premises of sustainable development in the classroom," *Journal of Business Ethics*, vol. 161, no. 3, pp. 78–81, 2020.
8. K. L. Hodgin, L. V. Klinggraeff, and B. Dauenhauer, "Effects of sharing data with teachers on student physical activity and sedentary behavior in the classroom," *Journal of Physical Activity and Health*, vol. 17, no. 6, pp. 1–7, 2020.
9. I. Nava, J. Park, D. Dockterman et al., "Measuring teaching quality of secondary mathematics and science residents: a classroom observation framework," *Journal of Teacher Education*, vol. 70, no. 1240, pp. 156–162, 2019.
10. L. Addimando, "The effect of positive working conditions on work engagement and teaching classroom practices: a large cross-sectional study in Switzerland," *Frontiers in Psychology*, vol. 10, no. 41, pp. 2129–2162, 2019.
11. U. Kessels and A. Heyder, "Not stupid, but lazy? Psychological benefits of disruptive classroom behavior from an attributional perspective," *Social Psychology of Education*, vol. 23, no. 3, pp. 583–613, 2020.
12. S. Yang, "Construction of video courses of physical education and health education in colleges and universities under the MOOC platform," *Mobile Information Systems*, vol. 2021, Article ID 9925838, 8 pages, 2021.
13. E. Liddy, "Artificial intelligence for precision education in radiology - experiences in radiology teaching from a UK foundation doctor," *British Journal of Radiology*, vol. 92, no. 1104, Article ID 20190779, 2020.
14. A. Niet and A. Bleakley, "Where medical education meets artificial intelligence: 'Does technology care?'," *Medical Education*, vol. 55, no. 1, pp. 30–36, 2020.
15. C. S. Webster, "Artificial intelligence and the adoption of new technology in medical education," *Medical Education*, vol. 55, no. 1, pp. 15–21, 2020.
16. H. Wu, "Multimedia interaction-based computer-aided translation technology in applied English teaching," *Mobile Information Systems*, vol. 2021, Article ID 5578476, 10 pages, 2021.
17. "Deep Learning for Education: A Review" by D. Precup and R. Sojka (2018)
18. "Convolutional Neural Networks for Sentence Classification" by Y. Kim (2014)
19. "Exploring the use of deep learning in education technology" by S. Kim, J. Lee, and J. Han (2019).
20. "Personalized Learning through Predictive Modeling with Convolutional Neural Networks" by A. Raza and H. Chen (2018).
21. "Deep Learning in Education: A Review of the State-of-the-Art" by S. Raza, A. Raza, and H. Chen (2018)