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Convolutional Neural Network and its Role in Medical Imaging

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Abstract

Artificial intelligence (AI) is an upcoming trending branch that has a crucial role to play in the field of medical imaging. A convolutional neural network (CNN) is a type of feed-forward model of the network that allows self-learning by the proposed algorithm. In the field of medicine, where imaging plays a crucial role in assisting the diagnosis of pathology, AI, like CNN, might play an important role in assessing and classifying the disease. In the current manuscript, we describe the structure and function of CNN with an emphasis on its role in medical imaging.

KEY WORDS

Convolutional neural network; CNN; Healthcare; Radiodiagnosis; Medicine.

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Introduction

A convolutional neural network (CNN) is a type of neuronal network inspired by mammalian vision neurons, where the higher-order neurons are meant to perform different and evolved functions compared to the neurons in the lower order. It is classified under artificial intelligence (AI) along with deep learning and machine learning. CNN comprises various layers in the network, and each layer provides an output that acts as an input to the next layer. This is known as the feed-forward network [1][2].

CNN has been widely used in many imaging studies of various systems of the human body, including the brain, breast, abdomen and pelvis, musculoskeletal system, and chest, and has provided results that have good sensitivity and specificity in many fields. This manuscript describes the convolutional neural network, its architecture, and its use in the field of medical imaging.

Discussion

Convolutional Neural Network (CNN) algorithms are used to solve computer vision tasks and are classified under artificial intelligence (AI). AI is a broad umbrella term consisting of machine learning (ML), deep learning (DL), and CNN [1]. Algorithms to solve problems requiring human intelligence are described by AI. ML is a subclass of AI that deals with providing computers with the ability to learn without being programmed. Humans choose the visual data representing the imaging features (acuteness of mass or Hounsfield units histogram), and based on the imaging features, data is classified using appropriate statistical analysis in classical ML. DL is a subclass of ML where humans are not required to select imaging features; rather, the algorithm learns the imaging features that are best required for classifying the data on its own. Artificial neural networks form the basis for most of the DL algorithms [2]. CNN is a subclass of artificial neural networks that assumes the inputs are images [3].

A Nobel prize-winning work by Hubel and Wiesel in understanding a cat's visual cortex pathway forms the inspiration for CNN [4]. Hubel and Wiesel understood the hierarchical nature of the visual process, where a neuron at the beginning (simple cells) of the pathway would respond to simple features like lines at different angles. Higher-order neurons (complex cells) would respond to complex combinations of simple features, such as two lines at right angles to each other. This was tried to be replicated in the CNN, creating a neuronal map by using a process called convolution, which involves the point multiplication of the small matrices of weights across the entire image [1].

Artificial neuronal network:

An understanding of the technology of artificial neurons can be done by understanding the biological neuron. The components of the biological neuron involve an axon, a cell body, and dendrites. The dendrites receive the signals, and the cell body performs the function. The neuron produces an action potential if the sum of all the received signals is above a certain threshold. Neuronal axons transmit the signal to the other dendrites by using synapses [5].

Multiple artificial neurons comprise and form the artificial neural networks. Input signals, x1, x2, ..., xn, are received by the artificial neurons and are multiplied by the synapse's strength called termed weights (ω). Similar to the action potential production by a biological neuron, the neuron firing in the artificial neuron depends on the weighted sum of its input, which provides the activation function output. *f* represents a nonlinear activation function that is incorporated into the sum of the multiplication of the weights and inputs. The rectified linear unit (ReLU) function is currently the most widely used nonlinear function that selects the maximum of either z or 0 [2].

A collection of such neurons connected in an undirected graph forms artificial neural networks. The neurons have a multilayered arrangement where the adjacent layer neurons have a paired connection, while the neurons in the same layer are not connected. Hence, the output of a few neurons has the propensity to act as an input of the other neurons [6]. A neural network comprises three layers: (i) Input layer – data is provided to the network through the input layer; (ii) Hidden layer – data from the input layer is provided to the multiple hidden layers where the output is generated using matrix multiplication; (ii) Output layer – output data from the hidden layers is provided to the output layer which uses logistic functions to convert the output into the probability scores [7].

CNN architecture

It is an extension of the artificial neural network that is used predominantly to bring out details from the grid-like matrix dataset. It consists of an input layer that receives the provided data, a convolutional layer that extracts the details from the provided data using filters, a pooling layer that reduces computation by downsampling the data, and a fully connected layer that brings the data from the previous layer to the output layer. This is a type of feed-forward model where the output data of one layer is transferred to the next layer, which acts as the input data [7].

The data is then assessed for errors using software like square loss error, cross-entropy, etc. This is important to assess the functioning of the network. Following the error assessment, backpropagation of the model is done by calculating the derivatives. This is an important step to minimize the loss of data [8].

Applications of CNN in imaging:

CNN is used in research in many imaging fields, with MRI and neuroimaging being the most common selections and oncology being the most commonly used imaging field. The most widely used task for computer vision was selection [5]. The use of CNN has been incorporated into many imaging fields of various human organs, including the brain, chest, abdomen and pelvis, breast, and musculoskeletal system [5].

(i) Neuroimaging: The main focus of the usage of CNN in neuroimaging is anatomic structure segmentation [9][10][11]. Chen H et al [9] performed a study using 20 segmented magnetic resonance imaging (MRI) scans where the data was segmented into four parts: cerebrospinal fluid, white matter, gray matter, and the background. The study showed the Dice coefficients of 0.84-0.89. Few studies have been published on the use of the CNN network for the evaluation of brain lesions with a focus on glioma [12][13][14]. Few studies have been conducted on the use of CNN on the neurodegenerative diseases. CNN has been used for the Alzheimer's disease classification and assessment of mild cognitive impairment using MRI and computed tomography (CT) scans to look for a non-invasive biomarker for determining the patients that may benefit from the early treatment [15][16].

(ii) Chest: Chest abnormalities, including infectious diseases, parenchymal diseases, and cancer, have been evaluated by researchers using CNN. The most widely used research was for detecting lung nodules in both CT scans and chest radiographs [17][18][19]. Few researches have been conducted for the assessment of lung nodules using LUNA16, which used a public Lung Image Database Consortium, where the lung nodules were classified into either malignant or benign by some researchers or were classified based on the nodule location, calcification, and density by other researchers [17][20]. A few studies have been conducted to identify and assess chronic obstructive lung disease and interstitial lung disease [21][22][23]. The research was conducted by Cicero M et al. on a large private data set of 35,038 chest radiographs where the radiographs were classified into either normal or showing one of the features: consolidation, pulmonary edema, pneumothorax, pleural effusion, or cardiomegaly. The receiver operating characteristic curve of 0.85-0.96 was obtained for different findings [24]. Additionally, the CNN methods have been used to evaluate the chest radiographs for the assessment of pulmonary tuberculosis [25][26].

(iii) Abdomen and pelvis: The organ segmentation studies have been conducted for the evaluation of abdominal organs like liver, kidney, spleen, urinary bladder, and prostate based on the imaging features of CT and ultrasound (USG) [27][28][29][30][31]. The liver has been the prime imaging organ to be assessed using CNN. A few studies have been performed for the segmentation of the liver, while others have been performed to classify the pathological liver lesions on CT [32], assess and classify the liver metastasis [33], and stage liver fibrosis using an MRI [34]. A few studies have been done to assess the role of CNN in evaluating rectal, bladder, and prostate carcinoma [35][36][37]. The usage of CNN for assessment of gastrointestinal pathologies is scarce, with one study done using CT to detect colitis [38] and the other study done using abdominal radiographs to assess small bowel obstruction [39].

(iv) Breast: Detection and classification of breast carcinoma using mammography films has been the most widely used application of CNN in detecting breast pathologies [40][41][42][43]. The researchers chose the criteria for classification based on the parameters accepted by the radiologists, including microcalcification detection [44], differences in symmetry, and temporal changes [45]. Most of the studies have used the BI-RADS (Breast Imaging Reporting and Data System) criteria for the classification of benign and malignant breast lesions [46]. A study was done by Carneiro et al [41] using a public dataset of Digital Database for Screening

Mammography and INbreast for 1090 mammographic films, and an algorithm was presented that acquires the segmentation maps from the microcalcifications and breast lesions to classify the complete scan. The area under the receiver operating characteristic curve for the study was 0.86.

(v) Musculoskeletal system: The most commonly incorporated function of the CNN in the musculoskeletal system is the assessment of bone age [47][48], detection of spinal level [49][50], detection of spinal pathology [51], detection of osteoarthritis [52], and detecting fractures [53]. A study conducted by Larson et al [47] on 12,000 left-hand radiographs concluded to be accurate, similar to that of an expert radiologist. A study was conducted by Mbarki et al. [54] to evaluate the status of the lumbar intervertebral disc from the level of L1-L2 to L5-S1. It classified the discs into normal or herniated discs. A CNN software VCG16 was used for the study on more than 200 cases, and the accuracy was 94%.

The nucleus pulposus in the Intervertebral disc is a gelatinous substance composed of 66-86% water, collagen, and proteoglycans. The degeneration of the disc occurs with increasing age or other factors like heavy weightlifting, causing a change in the biochemical disc properties. The degeneration of the disc is the most common cause of lower back pain, and MRI is the non-invasive imaging modality of choice for the assessment of disc degeneration. The protocol for imaging the lumbar spine includes T1WI and T2WI. The Apparent Diffusion Coefficient (ADC) sequence is an MRI sequence that demonstrates the free diffusion of unbound water [55][56][57]. The scope of the use of CNN in imaging the lumbar intervertebral disc is to assess the amount of water in the disc and provide a numerical value for it, thus classifying the disc degeneration based on quantification of the water content retained by the disc.

Conclusion:

With technological advancement, artificial intelligence plays a crucial role in improving healthcare. With advancements in the development of software for the evaluation and classification of various pathologies, CNN plays a very important role. The imaging of the brain, musculoskeletal system, breast, and other organs has been assessed by CNN in various studies and has shown promising results. However, no study has been performed to date incorporating artificial intelligence where the intervertebral disc quantification can be done using ADC sequence. Hence, this can be a future trend that might help radiologists and clinicians assess the degree of degeneration of the intervertebral disc and start early treatment in the required cases. **R**

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