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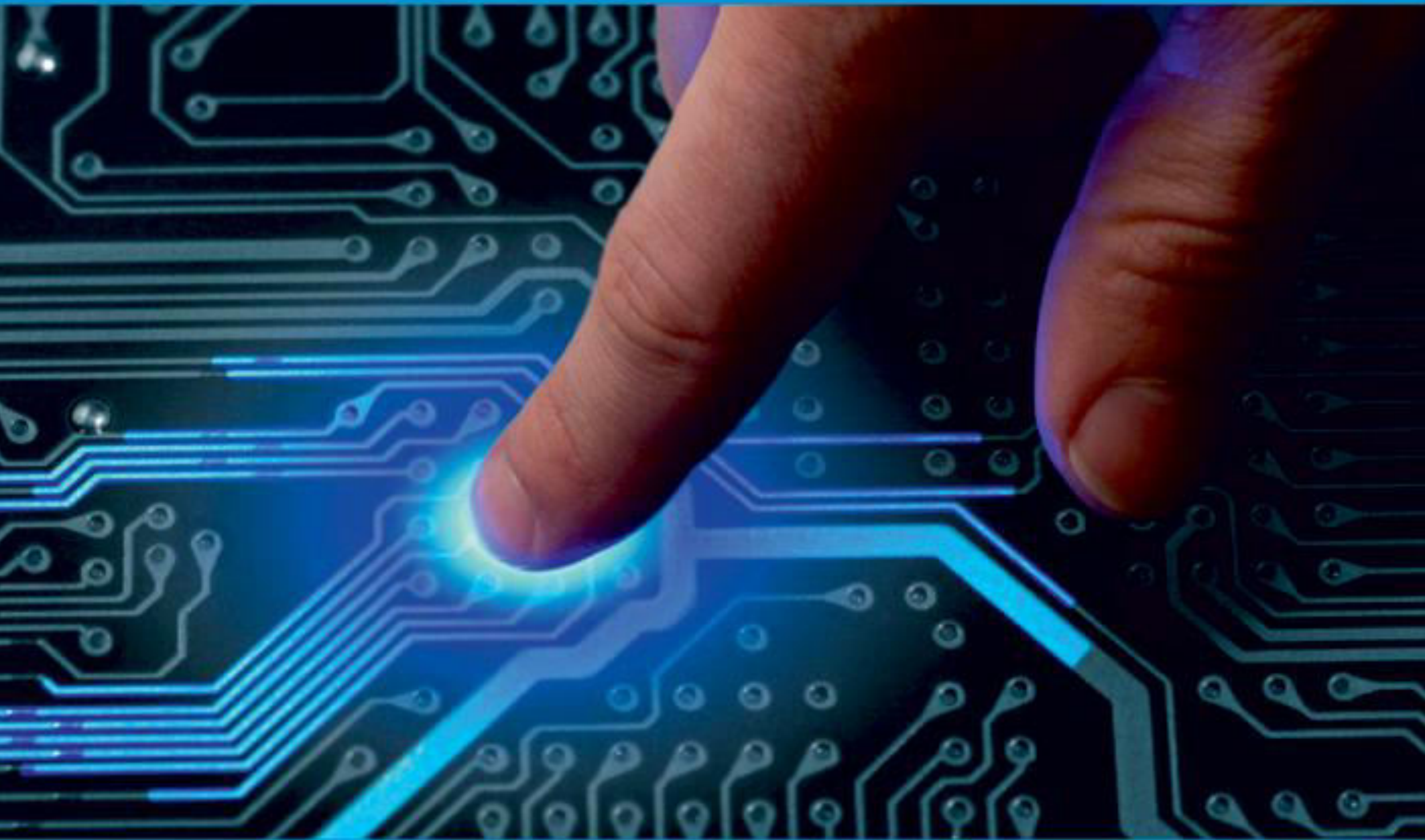

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# Deep Learning Algorithm for System's Health

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**ABSTRACT:** Machine learning is quickly becoming an important tool for diagnosis and prognosis of different medical conditions. Complex input output mappings areas signed in deep learning, which is developed based on machine learning approach. Due to its efficiency and similarity to the working of the human brain, deep neural networks area preferred method of processing and analysing medical data. In addition to diagnosis, deep learning is used to study the boost of disease, develop a personalized treatment plan and for over all patient management. This chapter discusses the architecture and working of deep neural networks and focus on its application in the detection and treatment of various diseases like cancer, diabetes, Alzheimer's disease. Deep learning algorithm are highly increasing algorithms that learn about the image that we discussed earlier by passing it through each neural networks layer deep trained layers are programmed to find special object like dogs, trees, utensils etc..

**KEYWORDS:** Deep neural network, Architecture, Disease

## I. INTRODUCTION

Machine learning (ML) means training a computer to make decisions based on preceding facts. The learning process is known as teaching. New data can be given to a trained model to make informed decisions. The more data stuffed to the computer for training, the more complex and specific rules and more exact the predictions. Deep learning (DL) is a special case of artificial neural networks a machine learning algorithm encouraged from human brain. A neural network processes information in away a like to the working of human brain, with several neurons connected in various layers. Deep networks have the capacity to process huge data and generate rules for processing new data. The deep-learning method is called an artificial neural network. It is a unique example of artificial neural networks, a technique for machine learning that was inspired by the human brain. Notice-able improvements in the area have been made as relates to the capacity of machines to grasp and modify data, including voice, style, and picture data....

Deep learning algorithms are powerfully made to run through several layers of neural networks, which are nothing but a set of decision making networks that are former education to serve a task. We mainly used deep learning and the algorithms that work behind deep learning. Dynamic pace with vision to create intelligent software that can recreate it and function like a human brain. A person needs high clarity with mathematical functions discussed in some of the algorithms. These functions are so decisive that the working of these algorithms mostly depends on the computations done by using these functions and formula. Deep learning engineers knows all of these algorithms are highly praised for beginners to understand these algorithms earlier moving ahead into artificial intelligence(AI) Different deep learning approaches have been significantly reviewed and discussed in recent years deep networks have been shown to be successful for system vision task because they can extract appropriate feature while join performing insight

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## II. DEEP LEARNING


fig(a): Deep Learning

Deep learning is a branch of machine learning which is completely based on artificial neural networks, as neural network is going to imitate the human brain so deep learning is also a kind of imitation of human brain. In deep learning, we don't need to clearly program everything. The concept of deep learning is not new. It has been around for some years back now. It's on hype nowadays because earlier we did not have that much processing power and a lot of data. A sin the last 20 years, the extracting power increases exponentially, deep learning and machine learning came in the picture .A formal definition of deep learning is-neurons Deep Learning is a subdivision of Machine Learning that is based on artificial neural networks (ANNs)with multiple layers also known as deep neural networks(DNNs).These neural networks are stimulate by the structure and function of the human brain, and they are designed to learn from large amounts of data in an unsupervised or semi-supervised manner In human brain approximately 100 billion neurons all together this is a picture of an individual neuron and each neuron is attach through thousand of the neighbours. The question here is how do were create these neurons in a computer. So, we create an artificial structure called an artificial neural net where we have nodes or neurons. We have some neurons for input value and some for output value and in between, there may be lots of neurons inter connected in the hidden layer.

## III. ARCHITECTURE

**1. Deep Neural Network :** It is a neural network with a resolute level of complexness(having multiple hidden layers in between input and output layers).They are capable of modelling and processing non-linear relationships.

**2. Deep Belief Network:** (DBN) it is a class of Deep Neural Network. It is multi-layer belief networks. Steps for performing DBN:

**a**. Learn a layer of attribute from clear units using Contrastive Divergence algorithm.

**b**. Treat activations of previously trained attribute as visible units and then learn features of features.

**c**. Finally, the hole DBN is trained when the learning for the final unseen layer is achieved.

**3. Recurrent:** (perform same task forever element of a sequence) Neural Network Allows for parallel and sequential computation. Similar to the human brain (large feedback network of connected neurons).They are able to remember important things about the input they received and hence enables them to be more accurate.

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## IV. WORKING

First, we need to identify the certain problem in order to get the correct solution and it should be understood, the feasibility of the Deep Learning should also be checked (whether it should fit Deep Learning or not).

Second, we need to identify the related data which should correspond to the certain problem and should be prepared accordingly.

Third, Choose the Deep Learning Algorithm appropriately. Fourth, Algorithm should be used while training the dataset. Fifth, Final testing should be done on the data set.

Tools used :Anaconda,Jupyter,Pycharm,etc.Languagesused:R,Python,Matlab,CPP,Java,Julia

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Fig(b): PY Charm fig(c): JUPYTER

## V. APPLICATIONS OF DEEP LEARNING IN MACHINE HEALTH MONITORING:

The conventional multilayer perceptron (MLP) has been applied in the field of machine health monitoring for many years the deep learning techniques have recently been applied to a large number of machine health monitoring systems.

fig(d): Monitoring

The layer-by-layer pretraining of deep neural network (DNN) based on Auto-encoder or RBM can ease the training of DNN and improve its discriminative power to characterize machinery data. Convolution neural network and recurrent neural networks provide more advanced and complex compositions mechanism to learn representation from machinery data. In these DL-based MHM S systems, the top layer normally represents the targets. For diagnosis where targets are discrete values, soft max layer is applied. For prognosis with continuous targets, liner regression layer is added. What is more, the end-to-end structure enables DL based MHMS to be constructed with less human labour and expert knowledge therefore these models are not restricted to specific machine specific or domain.

In the following, a brief survey of DL-based MHMS is presented in these above four DL architectures: AE, RBM, CNN and RNN. A. AE and its variants for machine health monitoring AE models, especially stacked DA, can learn high-level representations from machinery data in an automatic way. Sun et al. proposed a one layer AE-based neural network to classify induction motor faults. Due to the restricted size of training data, they focused on how to prevent over appropriate. Not only the number of unseen layer was set to 1, but also dropout technique that masks portions of output neurons randomly was applied on the unseen layer. However, most of proposed models are based on deep architectures by stacking multiple auto-encoders. Lu et al. presented a detailed empirical study of stacked denoising autoencoders with three hidden layers for fault diagnosis of rotary machinery components. Specifically, in their experiments including single working condition and cross working conditions,

## VI.. RBM AND IT'S VARIANTS FOR MACHINE HEALTH MONITORING

In the section, some work focused on developing RBM and DBM to learn representation from machinery data. Most of works introduced here are based on deep belief networks (DBN) that can pretrain a deep neural network (DNN). In a RBM based method for bearing remaining useful life (RUL) prediction was proposed. Linear regression layer was added at the top of RBM after pretraining to guess the future root mean square (RMS) based on a lagged time series of RMS values. Then, RUL was calculated by using the predicted RMS and the total time of the bearing's life.

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Liao et al. proposed a new RBM for representation learning to predict RUL of machines. In their work, a new regularization term modelling the trend ability of the unseen nodes was added into the training objective function of RBM.

Then, unsupervised self-organizing map algorithm (SOM) was applied to converting the representation learned by the enhanced RBM to one scale named health value. Finally, the health value was used to predict RUL via a similarity-based life prediction algorithm. In a multi-modal deep support vector classification approach was proposed for fault diagnosis of gearboxes. Firstly, three modalities features including time, frequency and time-frequency ones were extracted from vibration signals. Then, three Gaussian-Bernoulli deep Boltzmann machines (GDBMS) were applied to addressing the above three modalities, respectively. In each GDBMS, the soft max Illustrations of the proposed SAE-DN for rotating machinery diagnosis in layer was used at the top.

After the pre training and the fine tuning processes, the contingency outputs of the soft max layers from these three GDBMS were fused by a support vector classification (SVC) framework to make the final prediction. Li et al. applied one GDBMS directly on the concatenation feature consisting of three modalities attributes including time, frequency and time-frequency ones and stacked one soft max layer on top of GDBMS to recognize fault categories. Li et al. adopted two layers DBM to learn deep representations of the statistical parameters of the wavelet packet transform (WPT) of raw sensory signal for gearbox fault diagnosis. In this work focusing on data fusion, two DBMs were applied on acoustic and vibratory signals and random forest was applied to fusing the representations learned by these two DBMs. Making use of DBN-based DNN, Ma et al. presented this framework for degradation assessment under a bearing accelerated life test.

The statistical feature, root mean square (RMS) fitted by Weibull distribution that can avoid areas of oscillation of the statistical parameter and the frequency domain attributes were extracted as raw input. To give a clear illustration, Shao et al. proposed DBN for induction motor fault diagnosis with the direct usage of vibration signals as input. Beside the evaluation of the final classification accuracies, t-SNE algorithm was adopted to visualize the learned representation of DBN and outputs of each layer in DBN.

They found the addition of hidden layer can increase the discriminative power in the learned representation. Fu et al. employed deep belief networks for cutting states monitoring. In the presented work, three different feature sets including raw vibration signal, Mel-frequency spectrum coefficient (MFCC) and wavelet features were fed into DBN as three corresponding various inputs, which were able to achieve robust comparative performance on the raw vibration signal without too much feature engineering. Tamil et al. proposed a multi-sensory DBN-based health state classification model.

The model was verified in benchmark classification problems and two health diagnosis applications including aircraft engine health diagnosis and electric power transformer health diagnosis. Tao et al. proposed DBN based multi sensor information fusion scheme for bearing fault diagnosis. Firstly, 14 time-domain statistical features extracted from three vibration signals acquired by three sensors were concatenated together as an input vector to DBM model. During pre-training, a predefined threshold value was introduced to determine its iteration number. In a feature vector consisting of load and speed measure, time domain features and frequency domain attributes was fed into DBN-based DNN for gearbox fault diagnosis.

In the work of Gan et al. built a hierarchical diagnosis network for fault pattern recognition of rolling element bearings consisting of two consecutive phases where the four different fault locations (including one health state) were firstly identified and then discrete fault severities in each fault condition were classified. In each phases, the frequency-band energy features generated by WPT were fed into DBN-based DNN for pattern classification. In raw vibration signals were pre-processed to generate 2D image based on omnidirectional regeneration (ODR) techniques and then, histogram of original gradients (HOG) descriptor was applied on the generated image and the learned vector was fed into DBN for automatic diagnosis of journal bearing rotor systems. Chen et al. proposed an ensemble of DBNs with multi-objective evolutionary optimization on decomposition algorithm (MOEA/D) for fault diagnosis with multivariate sensory data. DBNs with different architectures can be regarded as base classifiers and MOEA/D was introduced to adjust the ensemble weights to achieve a trade-off between accuracy and diversity. Chen et al. then extended this above framework for one specific prognostics task: the RUL estimation of the mechanical system. C. CNN for machine health monitoring

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In some scenarios, machinery data can be presented in a 2D format such as time-frequency spectrum, while in some scenarios, they are in a 1D format, i.e., time-series. Therefore, CNNs models are able to learn complex and robust representation via its convolutional layer. Intuitively, filters in convolutional layers can extract local patterns in raw data and stacking these convolutional layers can further build complex patterns. Janssens et al. utilized a 2D-CNN model for four categories rotating machinery conditions recognition, whose input is DFT of two accelerometer signals from two sensors that are placed perpendicular to each other.

## VII. CNN FOR MACHINE HEALTH MONITORING

In some sketch, machinery data can be presented in a 2D format such as time-frequency spectrum, while in some concept, they are in a 1D format, i.e., time-series. Therefore, CNNs models are able to learn complex and robust representation via its convolutional layer. Intuitively, filters in convolutional layers can extract local patterns in raw data and assembling these convolutional layers can further build complex patterns. Janssens et al. utilized a 2D-CNN model for four classification rotating machinery conditions recognition, whose input is DFT of two accelerometer signals from two sensors that are placed perpendicular to each other.

Therefore, Illustrations of the proposed DBN-DNN for assessment of bearing debasement in height of input is the number of sensors. The adopted CNN model contains one convolutional layer and a fully connected layer. Then, the top soft max layer is adopted for classification. In Babu et al. built a 2D deep convolution neural network to predict the RUL of system based on normalized variation time series from sensor signals, in which one dimension of the 2D input is number of sensors as the setting reported in. In their model, average pooling is adopted instead of max pooling. Since RUL is a continuous value, the top layer was linear regression layer. Ding et al. proposed a deep Convolution Network (Con Net) where wavelet packet energy (WPE) image were used as input for spindle bearing fault diagnosis.

To fully discover the hierarchical representation, a multiscale layer was added after the last convolutional layer, which concatenates the outputs of the last convolutional layer and the ones of the previous pooling layer. Guo et al. proposed a hierarchical adaptive deep convolution neural network (ADCNN). Firstly, the input time series data as a signal-vector was transformed into a 32×32 matrix, which follows the typical input format adopted by Le Net. In addition, they designed a hierarchical framework to recognize fault patterns and fault size. In the fault pattern decision module, the first ADCNN was adopted to recognize fault type. In the fault size evaluation layer, based on each fault type, ADCNN with the same structure was used to predict fault size.

## VII. CONCLUSION

In this paper we have handed a methodical overview of the state of the art DL grounded a MHMS deep literacy as a sub field of machine is serving as a ground between big ministry data and data driven MHMS. Thus, within the once four times, they have been applied in colourful machine health monitoring tasks. These proposed DL grounded MHMS or eptiomised according to four orders of DL armature as bus encoder models, confined Boltzmann machines models convolutoinal neural networks and intermittent neural networks. Since the instigation of the exploration DL grounded MHMS growing presto, we hope the dispatch about the capabilities of this DL ways especially representations learning for common ministry data and target vaticination for colourful machine health monitoring task, can be conveyed to compendiums. Through these former workshops , it can be set up that DL grounded MHMS don't bear expensive mortal labor and expert knowledge, i.e., the end to end structure is suitable to collude raw ministry data to target. Thus the operation of deep literacy models are not confined to specific kinds of machines which can be general result to address the machine health monitoring problems. Either , some explorations trends and implict unborn exploration.

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