Classics of Deep Learning Approach for Human Behaviour Ontology: A Survey

H. R. Divakar[1], Dr.B.R.Prakash[2]

[1]Assistant Professor, Dept. of MCA, PES College of Engineering, Mandya, India.

[2]Assistant Professor, Dept. of MCA, Sri Siddartha Institute of Technology, Tumkur, India.

Abstract -- *As being a human with all technological equipments we cannot predict the different mode of communication, reaction and predicted behaviour for the current situation. So, in case of health centre to represent their current health status using social networks, having different conventional methods, among them we have Ontology is one of the technology derived from WordSet where we can retrieve information form semantic web for the cross reference of the given input regarding health social activity of a person based on the posts in online social networks allowing access between persons and places, for this we have a tool called SMASH ontology which works on the basis of semantic web. Where it access the middle ware for the human personal behaviour factor and social co-relation factor, the best prediction accuracy permit the development of semantic parsers to ontology specific queries for deep learning as ORBM. Now a day's many online health information sites having human behaviour predictions done with the some of the tools like RBM, CRBM, SRBM, ORBM and follows.*

Keywords: *Semantic Web, Ontology, SMASH Ontology, Social networks, Deep learning, RBM, CRBM, SRBM, ORBM.*

I. INTRODUCTION

As a technical tendency we have different traits and tools to attempt high level abstraction of information in all the fields like machine learning, image processing as classification, filtering of image, audio as filtering noise out, video clustering and segmentation, as the same onto science relates more on text based search and prediction. The various cases of ontology for various domains are generated from semantic web. To make a better model of deep learning architectures like RBM to make a complete mortal view with the help of health social networks having ontology as a backbone[14].

The Deep learning is a subset of machine learning having a facet of neural networks. Xiaoqian Liu and Tingshao Zhu [1] states that the utilization of a deep learning algorithm to build a feature learning model for personality prediction. With the supporting rapid growth of arena like mobile computing, context aware computing, surveillance based security, unsupervised learning, where probability of the density may be labelled or unlabelled as a general unlabeled are more in case. The semi-supervised which are intended to divert the statistics of a problem with novel propose of graph based leaning frame work by coordination of semi supervised learning with multiple labels [12]. In supervised learning the algorithm wants to extract and analyse the training data to extrapolate to the general case for the unseen situations to semantic parsing which describes a task within the larger set of natural languages queries [3].

Deep learning [8] contains some basic terminologies which are defined with basic definitions as follows. It is a class of machine learning also known as subset of machine learning techniques, it has many layers of information processing phases represented in hierarchical architectures with WordSet may be misused, hence unsupervised feature learning for pattern classification or analysis is needed. Where Boltzmann Machine is a type of network with symmetrically connected like neuron units that has a capability to make decisions which has stochastic in nature either to be on or off to be with synonyms. While Restricted Boltzmann Machine (RBM) [2] is a special type of Boltzmann Machine consisting of combination of heterogeneous layers they are visible units layer and hidden units layer. It won't works with homogeneous layers like visible-visible or hidden-hidden. Deep neural network is multilayer network architecture consists of many hidden layers, where weights of those are fully connected and are frequently initialized with stacked RBMs. If we take a flat representation of domain specific parameters as an input, it neither or nor effects the domain knowledge of variants. The parameters are same in lexical representations like ontology's in the biomedical and health domain, human behaviour prediction in health social network. Which leads to research an ideology to pose the actual representation of personal characteristics captured in social networks where it having cognitive factors on individuals with their connected users, for this we have ORBM [3] Ontology Based Restricted Boltzmann Machine, ORBM+ [4] concerns for the accurate trustworthy problem solving methodology with the coordination of domain ontology [15] to increase the trust peak in an aggressive forward manner.

Section-I explains terminologies of various ontology's, Section-II explains survey of prediction of human behaviour in social networks, SRBM, ontology with deep learning, deep learning Neural Networks, parsing, ORBM, ORBM+, Bio-ontology's, Section-III concludes the appraisal of literature.

II. LITERATURE SURVEY

Now a day's layman, doctors and health care providers having busy schedule in their routine, hence they cannot be in regular communication. So using social media sites like facebook, LinkedIn, g+, etc., to solve this critical problem and to make ease communication between medical professionals and health care providers with patients as a media of questionnaires, sharing of information, opinions, feedback, and current updation with status of traits of medicines for interaction between them. From the web survey we have many communication media/servers like sermo also known as virtual doctors lounge for the trusted connection over the world, Orthomind having a motivation of improved patient care which expands the knowledge by connecting orthopaedic surgeons. QuantiaMD created as a platform for learning and collaboration among doctors with a millions of member conversations through phones, tablet, and laptop. MomMD is a community of female physician to board the discussions about healthcare related issues and compare average salaries with this lot of sites providing the facility through various social networks for doctor's usance.

According to Xiaoqian Liu and Tingshao Zhu [1] the usage of a deep learning algorithm to build a feature learning model for personality prediction, which could perform an unsupervised extraction of the Linguistic Representation Feature Vector (LVRF) activities it works as without supervision from text activity published in the Sina microblog where it gives an idea of user semantic information more objectively and comprehensively. There are many interdisciplinary researches of computational science and psychology [9, 10]. The Cross-media Auto-Encoder [11] to extract feature vectors, and identified user's psychological stress based in social network data. The LRVF could describe the user linguistic behaviour more objectively and comprehensively, and improve the accuracy of the personality prediction model. Here the deep learning algorithm used to construct an unsupervised feature learning model which can actively and objectively extract the LRVF from user's content published on the Sina microblog, it is considered as data set in his paper. Data collection is concerns about active user's selection criteria for choosing the effective and authentic samples. The collected data consists about user basic status information like age, gender, personal description and so on. In the survey of 2014–2015 there is an increase in users of microblogs. To filter out noisy data from the collected data as,

- If the total number of one's microblogs is more than the mean of total posts is considered as valid sample. This rule ensures that the user is an active user.

- To ensure the authenticity of the results of questionnaire, they set several polygraph questions in the questionnaire. The samples with unqualified questionnaires were removed.

- When the users filled out the questionnaire online, the time they took on each question were recorded. If the answering time was too short, the corresponding user was considered as an invalid sample. In their iterations, they set that the answering time should be longer than 2s.

For this they developed a simplified Chinese psychological linguistic analysis dictionary for the Sina microblog (SCLIWC) [12]. This dictionary was built based on LIWC 2007, in their dictionary they added thousands of words with 88 categories for emotion, meaning like positive word, negative word, family, money, punctuation etc., with the thorough analysis and observation it got a great difference of words belong to each category and others too. The personality prediction model is constructed by a linear regression algorithm. In order to improve the computational efficiency, for all traits of personality, they utilize the relatively simpler form of artificial neural network, autoencoder [13]. The figure.1 shows the basic structure of an autoencoder.

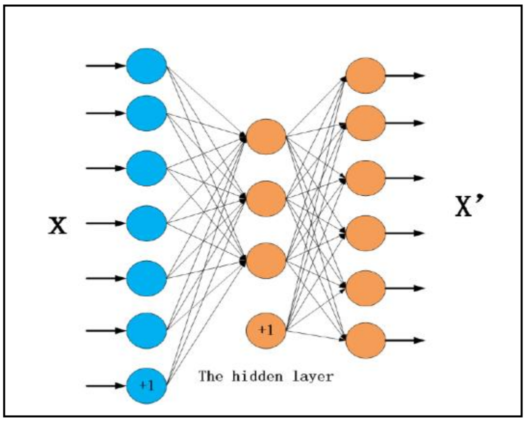

Fig 1: The basic structure of an autoencoder.

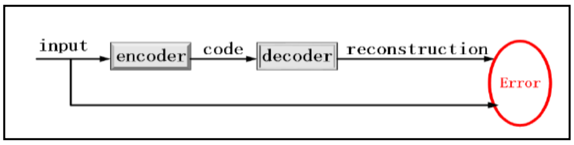

Fig 2: The training principle diagram of an autoencoder

In figure1, the mapping result Y as another representation of input X, it is assumed that the input X and the reconstructed X’ is the same. As shown in figure 2 a data set is inputted to encoder that encodes and sends to decoder where it reconstructs the data for parsing. For another method personality prediction is a supervised process. The linguistic behavior feature vectors are labeled by the corresponding scores of the big five questionnaire. They trained five personality prediction models based on linear regression algorithm using corresponding linguistic behavior feature vectors and labels that could improve the performance of personality prediction model they concluded as such.

NhatHai Phan, Dejing Dou et.al. [2] Presented a deep learning model known as Social Restricted Boltzmann Machine (SRBM) [2] for human behavior modeling and prediction in health social networks. In their proposed SRBM model, they incorporate self-motivation, implicit and explicit social influences, and environmental events together into three layers which are historical, visible and hidden layers.

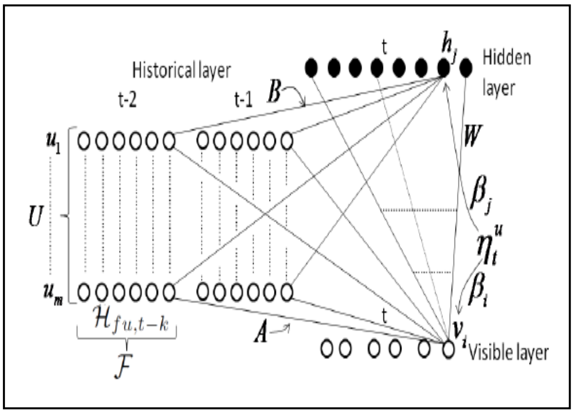

Fig 3: Social Restricted Boltzmann Machine.

The SRBM[2] model for human behavior prediction, takes the input data from an online social network consists set of users, where each user has set of individual features. The figure3 explains the historical layer of SRBM [2] is formed by considering self motivation. It is composed of many characteristics including attitudes, intentions, effort, and withdrawal which can all affect the motivation that an individual experiences [16]. Individual features are designed to capture self-motivation of each user consisting of key features like, Personal ability, Attitudes, Intentions, Effort, and Withdrawal. The hidden layer composed of implicit social influences and statistical explicit social influences they are, unobserved social relationships, unacquainted users, and the changing of the context [17]. The visible layer contains the environmental events such as the number of competitions and meet-up events are included in individual features. The SRBM model predicts the future activity levels of user more accurately and more stable than conventional methods.

With the coordination of SRBM NhatHai Phan, Dejing Dou et.al., introduce an ontology-based Restricted Boltzmann Machine (ORBM)[3] model for human behavior prediction in health social networks, which extends a well known deep learning method Restricted Boltzmann Machine(RBM). This is the first ontology-based deep learning approach in health informatics for human behavior prediction. Ontology [18, 19] is the formal specification of concepts and relationships for a particular domain. They have developed ontology for health social networks known as SMASH (Semantic Mining of Activity, Social, and Health data). Figure4 states the general workflow of ontology can be described as a top-down (knowledge-driven), followed by bottom-up (data-driven) validation and refinement approach. The SMASH ontology includes the following three modules, Biomarkers, Social Activities, Physical Activities.

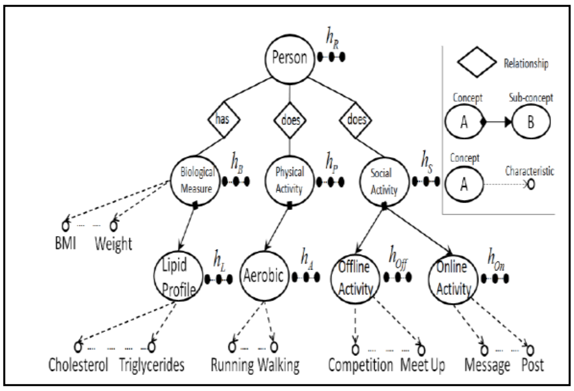

Fig 4: SMASH Ontology and its Hidden Variables.

With the help of ontology they got up an idea of ORBM as a novel approach to ontology-based deep learning model for human behavior prediction in health social networks. They contribute several novel techniques to deal with health social network ontologies considering characteristics like self-motivation, social influence, and environmental event modeling to build up a deep learning model to incorporate human behavior determinants as like in SRBM. The ORBM model predicts the future activity levels of users more accurately and stably than conventional methods.

NhatHai Phan, Dejing Dou et.al. proposed another ontology-based deep learning model $ORBM^+$ [4] for human behavior prediction over undirected and nodes-attributed graphs, they deal with human behavior prediction with explanations based on user representations, which have been learned from the SMASH ontology [3].

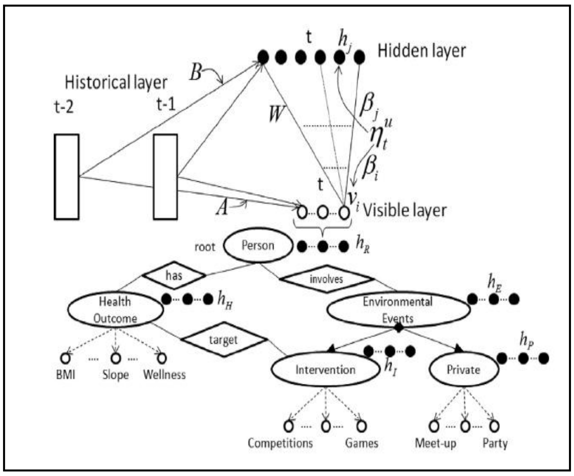

Fig 5: The $ORBM^+$ model.

The ORBM+[4] model utilizes user representations like self-motivation, social influences and environmental events as specified in SRBM and ORBM together in a human behaviour prediction model. In order to model self-motivation of a user, they first bipartitely connect the hidden and visible layers. All the historical variables are treated as additional observed inputs. The hidden layer can learn the correlations among the features and the effect of historical variables to capture self-motivation. The effect of environmental events is composed of unobserved social relationships, unacquainted users, and the changing of social context [2], [17]. The individual features of a user can be considered as the visible variables in the $ORBM^+$ model. The states of the hidden variables are determined both by the inputs they receive from the visible variables and from the historical variables. They states that ORBM+ model not only achieves significantly higher prediction accuracy, compared with the conventional models, but it also offers a deep understanding of the human behaviour determinants. ORBM+ is not only predicts human behaviours accurately, but also, it generates explanations for each predicted behaviour, it shows the tremendous effectiveness compared with conventional methods.

Charissa Ann Ronao, Sung-Bae Cho* [5] states that utilising the expert systems in accordance with OntoScience, a deep convolutional neural network is presented to perform efficient and effective human activity recognition using smart phone sensors draw from the inherent characteristics of activities and 1-D time series signals, as a meanwhile providing a directing to automatically and adaptively extract data with robust features from raw data. HAR[5] using smartphone sensors is a classic multi-variate time-series classification problem, which makes use of 1D sensor signals and extracts discriminative features from them to be able to recognize activities by utilizing a classifier[20]. Human activities have inherent hierarchical structures, and in the context of using sensors for HAR, are very prone to small translations at the input [21], [22]. The earlier refers to the characteristic of activities that can be broken down to simpler actions, while the latter denotes the different forms and styles people perform the same activities.

They propose a convent as the automatic feature extractor and classifier for recognizing human activities using smartphone sensors. The convolution operation effectively exploits the temporally-local dependency of time-series signals and the pooling operation cancels the effect of small translations in the input [21]. Using a multi-layer convent with alternating convolution and pooling layers, features are automatically extracted from raw time-series sensor data as shown in the figure.6, with lower layers extracting more basic features and higher layers deriving more complex ones.

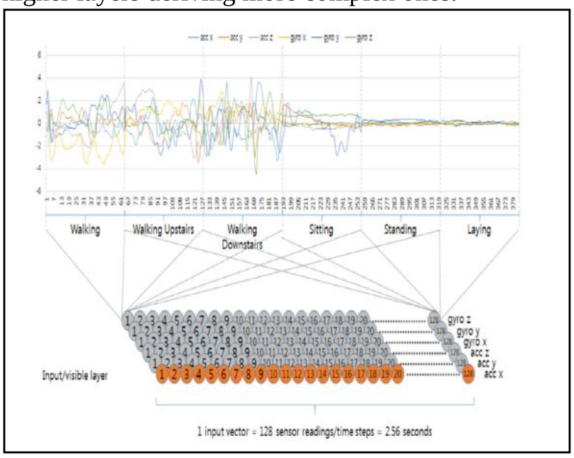

Fig 6:1D time-series multi-axes sensor input signal.

Research about HAR using deep learning techniques and their automatic feature extraction mechanism is very few. Among the first works that ventured in it are Plotz et al.[20], which made use of restricted Boltzmann machines (RBM), and Bhattacharya Nurmi, Hammerla et al.[23], Li, Shi, Ding & Liu[24], Vollmer, Gross, & Eggert[25], which both made use of slightly different sparse-coding techniques.

The above mentioned deep learning methods indeed automatically extract features from time series sensor data, but all are fully connected methods that do not capture the local dependency characteristics of sensor readings [26]. Zeng et al[27] and Zheng, Liu, Chen, Ge and Zhao[28] both applied convents to HAR using sensor signals, but the former assessed the problem of time-series in general and the latter only made use of a one-layered convent, which disregards the possible high advantage of hierarchically extracting features.

According to the results, convent outperforms other state-of-the-art data mining techniques in terms of performance on the test set. Lee. Y. S. et al., [29] experiment another activity dataset that was collected from three graduate students between 20 and 30 years old. They grasped the Android smartphone by hand for data collection. The sensor data were separated into windows of 128 values, with 50% overlap, the 128-real value vector stands for one example for one activity. The activities composed with 'stand', 'walk', 'stair up', 'stair down' and 'run'. They have provided sufficient training data which results in some examples for the test data. They achieved effective and efficient accuracy in performance comparing to the other competitive methods.

Edward Grefenstette, Phil Blunsom et al. [6] presented a novel deep learning architecture which provides a semantic parsing system through the union of two neural models of language semantics. This is exemplified by the growing popularity of products like Apple's Siri or Google's Google Now services. In turn, this creates the need for increasingly sophisticated methods for semantic parsing. This semantic representation varies significantly depending on the task context. Within the context of question answering they focus on semantic parsing typically aims to map natural language to database queries that would answer a given question. Kwiatkowski et al. [30] approach this problem using a multi-stage model. First, they use a CCG-like parser to convert natural language into an underspecified logical form (ULF). Second, the ULF is converted into a specified form, which can be used to lookup the answer to the given natural language question. Their model described here borrows heavily from two approaches in the deep learning literature. First, a noise-contrastive neural network similar to that of Hermann and Blunsom [31], [32] is used to learn a joint latent representation for natural language and database queries. Second, they employ a structured conditional neural language model to generate queries given latent representations. The Bilingual Compositional sentence model (BiCVM) of Hermann and Blunsom [31] provides a state-of-the-art method for learning semantically informative distributed representations for sentences of languages pairs from parallel corpora. The ability to jointly learn sentence embeddings like weakly aligned and strongly aligned, and to produce latent shared representations, will be relevant to semantic parsing pipeline.

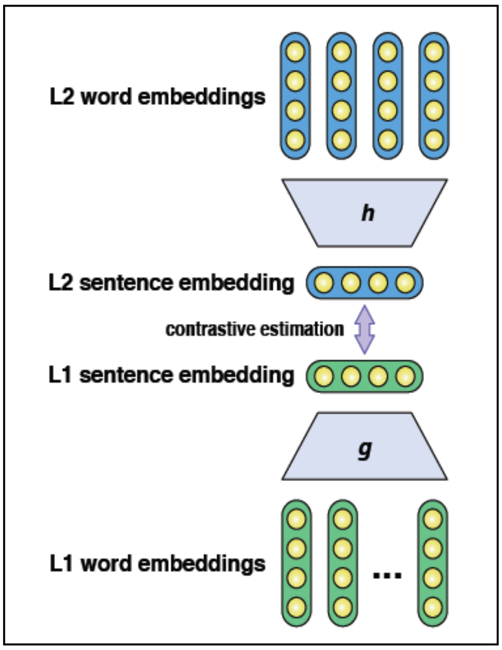

Fig 7: Diagrammatic representation of a BiCVM.

The BiCVM shown in figure.7 assumes vector composition functions, which map an order set of vectors onto a single vector to minimise the distance between composed representations and to avoid strong alignment between dissimilar cross-lingual sentence pairs; this error is combined with a noise-contrastive hinge loss. The particular training procedure for the model required aligned question/knowledgebase query pairs. There exist some small corpora that could be used for this task [33]. In order to scale training beyond these small corpora, they hypothesise that larger amount of training data could be obtained using a boot-strapping technique similar to Kwiatkowski et al. [30]. Further work will seek to determine whether this architecture can generate other structured formal language expressions, such as lambda expressions for use in textual entailment tasks.

III. CONCLUSION

With all the above survey we can predict large wing of ontology and its applications in all fields and with Further work will seek to determine whether this architecture can generate other structured formal language expressions, such as lambda expressions for use in textual entailment tasks.

REFERENCES

[1] Xiaoqian Liu and Tingshao Zhu. 2016. Deep learning for constructing microblog behaviour representation to identify social media user's personality. PeerJ Computer. Sci. 2:e81; DOI 10.7711/peerj-cs.81.

[2] N. Phan, D. Dou, B. peniewski, and D. Kil. 2015. Social restricted Boltzmann machine: Human behaviour prediction in health social networks. In ASONAM'15.

[3] N. Phan, D. Dou, H. Wang, B. peniewski, and D. Kil. 2015. Ontology-based Deep Learning for Human Behaviour Prediction in Health Social Networks. In ACM-BCB'15.

[4] N.Phan et al., 2016. Ontology-based deep learning for human behaviour prediction with explanations in health social networks, Information Sciences.

[5] Charissa Ann Ronao, Sung-Bae Cho. 2016. Human activity recognition with smartphone sensors using deep learning neural networks. Elsevier.

[6] Edward Grefenstette, Phil Blunsom, Nando de Freitas and Karl Moritz Hermann. 2014. A Deep Architecture for Semantic Parsing. Proceedings of the ACL workshop on Semantic Parsing, pages 22-27.

[7] H. Min et al, Applying an Ontology-guided Machine Learning Methodology to SEER-MHOS Dataset.

[8] Li Deng. Three Classes of Deep Learning Architectures and Their Applications: A Tutorial Survey.

[9] Zhang X, Hu B, Chen J, Moore P. 2013. Ontology-based context modeling for emotions recognition in an intelligent web. World Wide Web-internet and Web Information Systems 16(4):497-513 DOI 10.10007/s11280-012-0181-5.

[10] Chen J, Hu B, Moore P, Zhang X, Ma X. 2015. Electroencephalogram-based emotion assessment system using ontology and data mining techniques. Applied Soft Computing 30:663-674 DOI 10.1016/j.asoc.2015.01.007.

[11] Hujje L, Jia J, Quan G, Yuanyuan X, Jie H, Lianhong C, Ling F. 2014a. Psychological stress detection from cross-media microblog data using deep sparse neural network. In: Proceedings of IEEE international conference on multimedia expo. Piscataway: IEEE.

[12] Gao R, Hao B, Li H, GAO Y, Zhu T. 2013. Developing simplified Chinese psychological linguistic analysis dictionary for microblog. In: International conference on brain health informatics.

[13] Bengio Y. 2009. Learning deep architectures for AI. Foundations and Trends in Machine Learning 2(1):1-127 DOI 10.1561/2200000006.

[14] P. Smolensky, Information processing in dynamical systems: foundations of harmony theory, Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Vol. 1, MIT Press, 1986, pp. 194-281.

[15] T. Gruber. A translation approach to portable ontology specifications, Knowl. Acquisition 5(2) (1993) 199-220.

[16] R. M. Ryan and E. L. Deci. Intrinsic and extrinsic motivations: Classic definitions and new directions. Contemporary Educational Psycology, 25(1):54-67, 2000.

[17] N. A. Christakis. The hidden influence of social networks. In TED2010.2010. URL http://www.ted.com/talks/nicholas_christakis_the_hidden_influence_of_social_networks.

[18] T. R. Gruber. Toward principles for the design of ontologies used for knowledge sharing? International Journal of Human-computer Studies, 43(5):907-928, 1995.

[19] R. Studer, V. R. Benjamins, and D. Fensel. Knowledge engineering: principles and methods. Data & knowledge engineering, 25(1):161-197, 1998.

[20] Plotz. T., Hammerla. N. Y. & Olivier. P (2011). Feature learning for activity recognition in ubiquitous computing. In proceedings of international conference on artificial intelligence (IJCAI): Vol. 2 (pp. 1729-1734).

[21] LeCun. Y., Bengio. Y. & Hintion. G. (2015). Deep learning Nature. 521(7553), 436-444.

[22] Duong. T., Phung. D., Bui. H. & Venkatesh. S. (2009). Efficient duration and hierarchical modeling for human activity recognition. Artificial Intelligence, 173(7-8), 830-856.

[23] Bhattacharya. S., Nurmi. P., Hammerla. N. & Plotz. T. (2014). Using unlabeled data in a sparse-coding framework for human activity recognition. Pervasive and mobile computing. 15, 242-262.

[24] Li. Y., Shi. D., Ding. B. & Liu. D. (2014). Unsupervised feature learning for human activity recognition using smartphone sensors. Mining Intelligence and knowledge Exploration. 8891, 99-107.

[25] Vollmer. C., Gross. H. M. & Eggert. J. P. (2013). Learning features for activity recognition with shift-invariant sparse coding. In Proceedings of international conference on artificial neural networks and machine learning (ICANN): Vol. 8131 (pp. 367-374).

[26] LeCun. Y., Bengio. Y. (1998). Convolutional networks for images, speech, and time-series. In The handbook of brain theory and neural networks (pp. 255-258). The MIT Press.

[27] Zeng. M., Nguyen. L. T., Yu. B., Mengshoel. O. J., Zhu. J., Wu. P. & Zang. J. (2014). Convolutional neural networks for human activity recognition using mobile sensors. In Proceedings of international conference on mobile computing, applications and services (MobiCASE) (pp. 197-205).

[28] Zheng. Y., Liu. Q., Chen. E., Ge. Y. & Zhao. J. L. (2014). Time series classification using multi-channels deep convolutional neural networks. In Web-age information management. Lecture notes in computer science: Vol. 8485 (pp. 298-310). Springer.

[29] Lee. Y. S. & Cho. S. B. (2011). Activity recognition using hierarchical hidden markow models on a smartphone with 3D accelerometer. Hybrid Artificial Intelligent Systems. 6678. 460-467.

[30] Tom Kwiatkowski, Eunsol Choi, uoav Artzi, and Luke Zettlemoyer. 2013. Scaling semantic parsers with on-the-fly ontology matching. In proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1545-1556, Seattle, Washington, USA, October. Association for Computational Linguistics.

[31] Karl Moritz Hermann and Phil Blunsom. 2014a. Multilingual Distributed Representation without Word Alignment. In proceedings of the 2nd International Conference on Learning Represenations, Banff, Canada, April.

[32] Karl Moritz Hermann and Phil Blunsom. 2014b. Multilingual Models for Compositional Distributional Semantics. In Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Baltimore, USA, June. Association for Computational Linguistics.

[33] Quingqing Cai and Alexander Yates. 2013. Large-scale Semantic Parsing via Schema Matching and Lexicon Extension. In Proceedings of the Annual Meeting of the Association for Computational Linguistics (ACL).