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Identification of Diseases in Clinical Support System Using Extended Graph Convolution Neural Networks

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ABSTRACT:

Disease Identification, using Patient Symptoms is a important classical problem in clinical industry. Disease Identification using Natural Language Processing (NLP) requires efficient method for classifying medical data. Number of studies that applies convolution neural network for classification exists and some few flexible methods explored for graph convolution network for NLP based (text based) data classification . In this paper we proposed a method for NLP(text) based graph convolution neural network works both for document and record based structure. In this, labeled data are classified using supervised method and unlabeled data are classified using unsupervised method. We are using corpus based word co-occurrence and word relation processing, then learning process carry out by our proposed text GCN then both labeled and unlabeled data processed as per supervised and unsupervised learning. Text GCN also Reduce percentage of training data. This will increase the performance and robustness of GCN based text classification and prediction method.
Keywords : Graph Convolutional Network (GCN), Recurrent Graph Neural Network (RGNN) , Auto Encoder based Graph Convolution Network (AEGCN), , Deep Boltzmann Machine (DBM), Restricted Boltzmann Machine (RBM), Deep Belief Network (DBN).

1. Introduction

Clinical Support System or any automated medical support system, need efficient natural language processing based classifier and predictor. In this paper we are processing state-of-the-art classification method such as GCN graph convolutional network, Neural Network based text classification and prediction method, traditional text classification methods such as lexical features-> bag of words and n-gram and deep learning methods such as Convolution Neural Network (CNN) predecessor of GCN , RNN –Recurrent Neural Network and LSTM-Long and Short Term Memory Method.

Neural network based deep learning methods such as CCN,RNN,LSTM, works based on extracting semantic and syntactic information from the given text training data such as medical data. In recent days a new research on GCN plays important role in Data Classification. Embedding given data to graphs with CNN provide more efficient data classification and prediction. GCN also preserve Global Information structure of given data

In this research work we are proposing a brand new graph neural network text classification method for medical data classification.

2. Detailed Description OF Training Data

Training Medical Data is collected from Government General Hospital located at Ponneri, after getting permission from Tamilnadu Welfare Department. More than700 out patients are visiting the hospital for treatment every day. Patient details and symptoms are represented in data table 1 and the tablets for symptoms prescribed by doctors are represented in data table 2.

TABLE 1: Patient details and symptoms

S.NO	PATIENT NAME	Gender	AGE	SYMPTOM
1	Chinnaiyan	M	76	Dental problem
2	Perumal	M	75	Trouble Walking
3	Rithish	MC	6	Fever
4	Nagajothi	F	31	Trouble Walking &Arm/leg weakness
5	Jayamala	F	70	Backpain,Arthritis,Arm&leg weakness
6	Janarthanan	M	18	Arm 7 leg weakness
7	Krishnaveni	F	60	Neckpain
8	Surya	F	57	Head injury
9	Maari	M	80	Dental problem
10	Vengaiyen	M	50	Chest pain with exertion,Backpain,Arthritis
11	Mani Bharathi	M	18	Fever
12	Mani maran	M	21	Congestion/sneezing
13	Shiva lingam	M	68	Congestion/sneezing, wheezing/cough
14	Subbammal	F	60	Chest pain with exertion,wheezing/cough,back pain
15	Syed Moosa	M	66	Arthritis, Arm/leg weakness
16	Kalaiyarasan	M	41	Change in bowel habits, Loose stool/Diarrhea
17	Thanga Rasu	M	16	Head injury
18	venu	M	60	Head injury
19	Maari	M	60	Eyesight worsening,Double vision,Eye pain, Head injury
20	Manikandan	M	36	Ear pain
21	Munivel	M	60	Dental problem
22	Munniyammal	F	55	Trouble walking,Arm/leg Weakness,Backpain,Neckpain,Arthritis
23	valli	M	55	Fever
24	Mythili	F	38	Frequent stomach pain
25	Mithra	FC	3(1/2)	Fever & cough
26	Dilli	M	30	Arthritis
27	Safeena	F	30	Sneezing
28	Srinivasan	M	44	Back pain,Trouble Walking,Arm/leg weakness
29	Jalal	M	58	Arm/leg weakness
30	Maanikavasagam	M	65	Eye pain,Trouble walking,Arm/leg weakness,Arthritis
31	Velanganni	F	42	Headache,Backpain
32	Dhivan	M	16	Fevae & cold
33	Nivetha	F	25	Dental problem
34	Kamalesh	M	17	Sores
35	Baasha	M	48	Trouble walking
36	Angusamy	M	50	Arm/leg weakness
37	Durai	M	65	Head injury
38	Krishnan	M	60	Troble Walking,Arm &leg weakness
39	Lakshmi	F	38	Wheezing/cough
40	Sulochana	F	50	Backpain,Arm/leg weakness
41	Mukesh	M	13	Fever
42	Kalyani	F	32	Headache,Troble Walking
43	Hajeera	F	55	Arthritis
19/ 44	Mageshwari	F	40	Headache,Eye pain
45	Jayanthi	F	35	Headache,Troble Walking
46	Senthamarai	F	50	Aching muscles/joints
47	Santhi	F	55	Sores
48	Uma	F	45	Headache,Fever,cold
49	Viji	M	24	Frequent stomach pain,cold &cough
50	Mamshiga	FC	8	Alergy
51	Mahalakshmi	F	38	Headache
52	Muninathan	M	68	Aching muscles/joints
53	Sabari	M	15	Fever
54	Mageshwari	F	60	Backpain,Aching muscles/joints
55	Vinayak	M	13	Fever & Throat pain
56	Gowsiya	FC	3	Fever & Stomach pain
57	SenthilKumar	M	40	Seborrheic ,Iching
58	Udhaya	MC	4(1/2)	Dog Bite-ARV injection(Rabbis)
59	Prathab	M	32	Cough
60	Maniyammal	F	61	Cold & Cough
61	Heymanth	MC	12	Cycle accident
62	Sivaraj	M	29	Backpain
63	Sivaranjini	F	23	Headache & Neckpain
64	Selvi	F	53	Alergy

TABLE 2: Tablets for symptoms

TABLET 1	Dose	Frequency	TABLET 2	Dose	Frequency	TABLET 3	Dose	Frequency	TABLET 4	Dose	Frequency
Paracetamol	500mg	(1-1-1)	Antacid(Magnecium Trici		(1-0-1)	Amoxycicilin	250mg	(2-0-2)	B.complex		1-0-1
T.Dichlofenx sodium			T.Calcium			L.Omez		(-3)d			
Paracetamol		1/2 -1-1	B.Complex		1/2 -0-0	T.CPM		1/2 -1+1			
T.Brufa		(2-1-1)	T.Paracetamol		(1-1-1)	T.Ranitidine Hcl		(1-1-1)	T.Calcium		
T.Diclo			L.Omez			T.Calcium					
T.Paracetamol			T.NM								
Ranitide HCl			Brufen								
T.Brufen			T. Ranitide HCL								
T.Diclofenac Sodium		1-0-1	Magnicium Tri Sillicate		(1-1-1)	Amoxycillim		2-0-2	B.Complex		1-0-1
T.Diclofenac Sodium		(1-1-1)	C.Omez		(1-1-1)	B.Complex		(1-1-1)			
T.Paracetamol		1-0-1	T.CPM		(0-0-1)	B.Complex		1			
T.Paracetamol			T.CPM			T.BRUT			L.Omez		
C.Amoxycillin		2d	T.CPM		(0-0-1)	T.Paracetamol		(1-0-1)			
T.Brufen			Ranitidine HCL			L.Omez					
T.Brufen			Ranitidine HCL								
Omez		1-0-1	Magnicium Tri Sillicate		(1-1-0)						
C.Cephalexin	250mg	1-0-1	T.Metrosy		(1-1-1)	T.Paracetomol		(1-1-1)	C.Omez		1-0-1
T.Cform HC		3	T.CO-tri moxazole			DCM					
T.Paracetamol			T.CPM								
T.Brufen			L.Omez			T.Paracetamol					
T.Dichlofenx sodium		1-0-1	Magnicium Tri Sillicate		1-0-1	B.Complex		1-0-1	T.Calcium		1
T.Diclofenac Sodium		(1-1-1)	C.Omez		3d						
T.Ciproflaxicin		3	T.Brufin			T.Ranitidine HCL					
Par		1-0-1	Diccyclonin		1-0-1	Omez		1-0-1			
Paracetamol Syrup			Co-Trimoxazole syrup								
T.Dexamethasone			T.Diclofenac sodium			C.Omez					
T.Diclofenac Sodium		3d	T.Dexamethasone		3d	C.Omez		3d			
Diclofenax			Omez								
T.Diclo			T.Dexa			C.Omez					
Paracetamol		1-0-1	Diclofenac sodium		1-0-1						
Amoxycillin		(1-1-1)	T.Paracetamol		(1/2-1/2-1/2)	T.CPM		1/2-0-1/2			
Paracetamol		(1-1-1)	Amoxycillin		2-0-2	B.Complex		1-0-1	Metronydazole	200mg	(1-1-1)
Clotrimazole oint			T.Flucaezole		1-0-1	T.CPM		0-0-1			
T.Diclo			L.Omez								
T.Metformin HCL	500mg		T.Analodiplne	2.5g		T.Aspirin	150mg		T.Atorvastatin	10mg	
Paracetamol		1-0-1	B.Complex		(1-1-0)						
T.Diclofenaxin			L.Omepesarone								
T.CPM		1-0-1	T.Dexo		1-0-1						
T.Diclofenac Sodium		1-0-1	Ranitidine HCL		1-0-1	B.Complex		1-0-1	T.Calcium		1-0-0
Paracetamol		(1-1-1)	Amoxycillin		1-0-1	B.Complex		1-0-1	CPM		1/2-0-1/2
T.Diclofenac Sodium		1-0-1	Erythromycin		1-0-1	B.Complex		1-0-1	CPM		0-0-1
Diclofenax sodium		1-0-1	Paracetamol		1-0-1						
T.Diclofenac Sodium			Ranitide								
Ibuprofin			Omeprazole								
CPM			Clotrimazole oint								
T.CPM			T.Paracetamol			C.Amoxycillin					
Doxy			CPM			T.Paracetamol					
T.Phenenarmine mellate			Dexa		1/2-0-1/2	CPM		0-0-1			
T.Paracetamol		1-0-1	T.Ranitide		1-0-1	T.Dexamethasone		1-0-1			
C.Doxycycline		6	T.CPM		6	T.Paracetamol		6			
T.CPM		0-0-1/2	T.Metronidazole		1	T.Ciproflaxicin		1\2	T.Paracetamol		1/2-0-1/2
T.Paracetamol			T.Ranitidine								

3. Related and Recent Works

3.1 Recurrent Graph Neural Networks (RGCN)

This RGCN Recurrent Graph Neural Networks Capture or Extracts Contextual Information with Recurrent Graph Mode. RGCN can also capture Contextual Information and also preserve word order information.

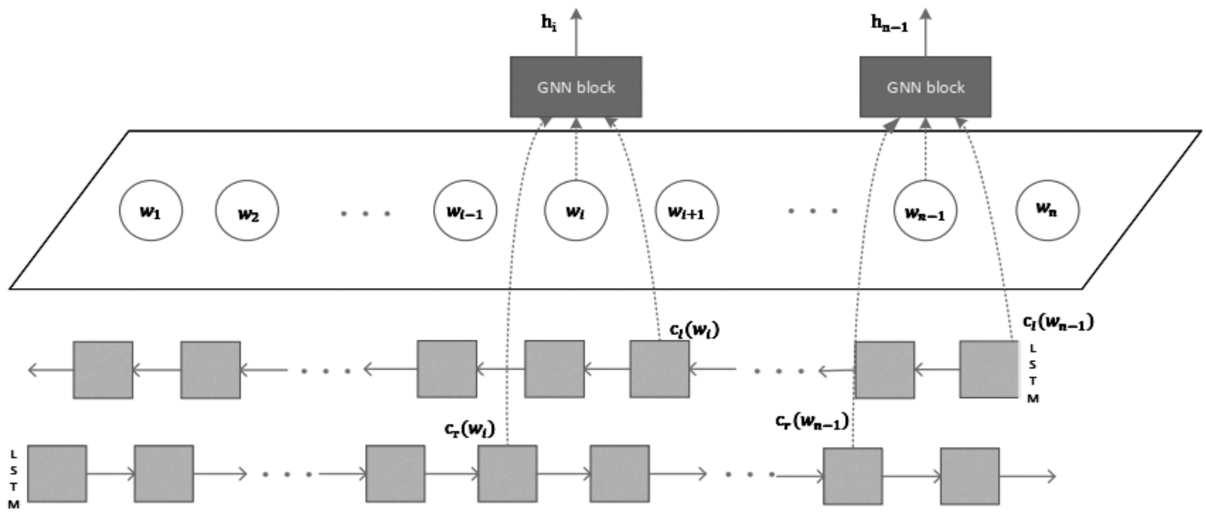

Figure 1 Structure of Recurrent Graph Neural Networks

3.2 Auto Encoder based Graph Convolution Networks (AEGCN)

Auto Encoder Based GCN Model uses , perfect layer wise propagation rules ,then uses first order approximation of convolutions to graph. AEGCN is Capable of Encoding both graph structure and also node features in semi-supervised classification

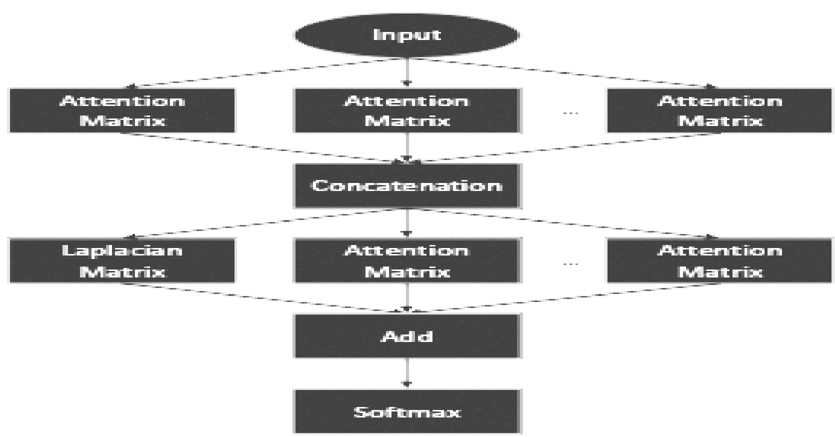

Figure 2 Architecture of AEGCN –Auto Encoder Based Convolution Network

3.3 Spatial Temporal Graph Convolution Network (STGCN)

Novel Spatial Temporal Deep Learning Network –Attentive diffusion Convolution can automatically capture carious spatial dependencies then this model using following methods such as attentive diffusion convolution and cascade LSTM block .

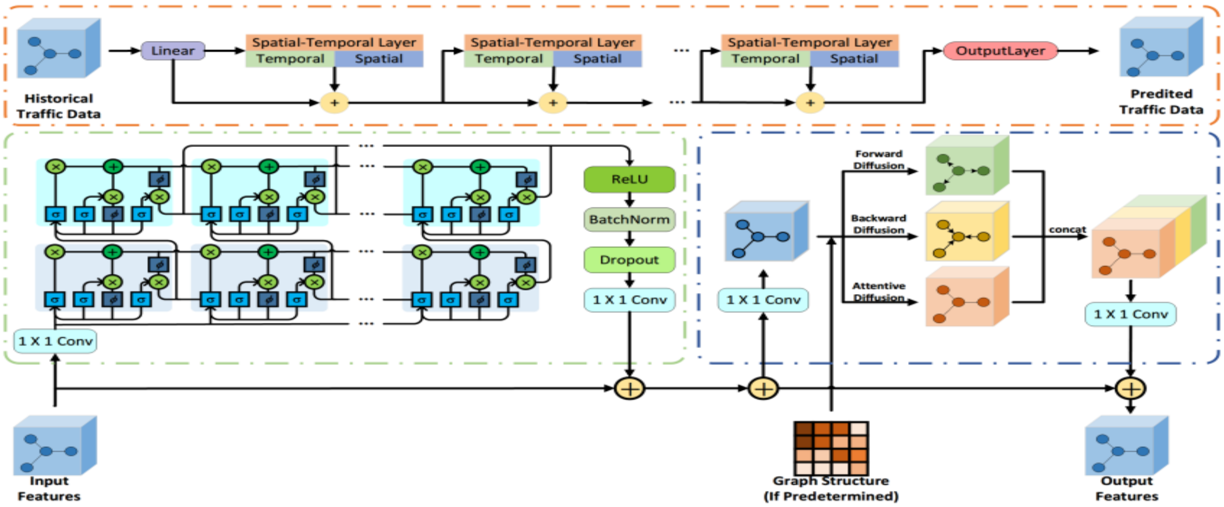

Figure 3 Architecture of STGCN

4. Implementation and Testing

4.1 Data Normalization-Cleaning and Conversion

Data Cleaning is need for every data set, before processing to any algorithm. Data cleaning steps involves duplicate reduction, nil data rectification and data remap. In this research work we have trimmed and converted suitable data for our training method or testing framework.

Table.3. Cleaned data

DISEASE ID	DISEASE NAME	ADD DESCRIPTION	DISEASE ID	SYMPTOM NAME
1001	GUSTROINTESTINAL BLEEDING	GUSTROINTESTINAL BLEEDING	1001	BLEEDING
1001	GUSTROINTESTINAL BLEEDING	GUSTROINTESTINAL BLEEDING	1001	RED COLORED VOMIT
1001	GUSTROINTESTINAL BLEEDING	GUSTROINTESTINAL BLEEDING	1001	COFFEE GROUNDS COLORED VOMIT
1002	FOOD POISONING	FOOD POISONING	1002	VOMITING
1002	FOOD POISONING	FOOD POISONING	1002	DIARRHEA
1002	FOOD POISONING	FOOD POISONING	1002	PAIN
1003	GASTROENTERITIS	STOMACH FLUE	1003	VOMITING
1003	GASTROENTERITIS	STOMACH FLUE	1003	PAIN
1003	GASTROENTERITIS	STOMACH FLUE	1003	BLOATING

1003	GASTROENTERITIS	STOMACH FLUE	1003	DECREASED APPETITE
1003	GASTROENTERITIS	STOMACH FLUE	1003	DIARRHEA
1003	GASTROENTERITIS	STOMACH FLUE	1003	RED COLORED VOMIT
1004	GENERALIZED ANXIETY DISORDER	GENERALIZED ANXIETY DISORDER	1004	CHILLS
1004	GENERALIZED ANXIETY DISORDER	GENERALIZED ANXIETY DISORDER	1004	PAIN
1004	GENERALIZED ANXIETY DISORDER	GENERALIZED ANXIETY DISORDER	1004	ANXIETY
1004	GENERALIZED ANXIETY DISORDER	GENERALIZED ANXIETY DISORDER	1004	DIZZINESS
1004	GENERALIZED ANXIETY DISORDER	GENERALIZED ANXIETY DISORDER	1004	VOMITING
1004	GENERALIZED ANXIETY DISORDER	GENERALIZED ANXIETY DISORDER	1004	AGITATION
1005	INTESTINAL LIEUS	INTESTINAL LIEUS	1005	PAIN
1005	INTESTINAL LIEUS	INTESTINAL LIEUS	1005	DECREASED APPETITE
1005	INTESTINAL LIEUS	INTESTINAL LIEUS	1005	CONSTIPATION
1005	INTESTINAL LIEUS	INTESTINAL LIEUS	1005	VOMITING
1005	INTESTINAL LIEUS	INTESTINAL LIEUS	1005	STOMACH CRAMPS
1006	IRRITABLE BOWEL SYNDROME	IRRITABLE BOWEL SYNDROME	1006	BLOATING
1006	IRRITABLE BOWEL SYNDROME	IRRITABLE BOWEL SYNDROME	1006	DIARRHEA
1006	IRRITABLE BOWEL SYNDROME	IRRITABLE BOWEL SYNDROME	1006	FREQUENT URGE TO HAVE BOWEL MOVEMENT
1006	IRRITABLE BOWEL	IRRITABLE BOWEL	1006	INCREASED

	SYNDROME	SYNDROME		PASSING GAS
1006	IRRITABLE BOWEL SYNDROME	IRRITABLE BOWEL SYNDROME	1006	PAIN
1006	IRRITABLE BOWEL SYNDROME	IRRITABLE BOWEL SYNDROME	1006	CONSTIPATION
1006	IRRITABLE BOWEL SYNDROME	IRRITABLE BOWEL SYNDROME	1006	FREQUENT BOWEL MOVEMENT
1007	NARCOTIC ABUSE	OPIATE ADDICTION	1007	PAIN
1007	NARCOTIC ABUSE	OPIATE ADDICTION	1007	CONFUSION
1007	NARCOTIC ABUSE	OPIATE ADDICTION	1007	CONSTIPATION
1007	NARCOTIC ABUSE	OPIATE ADDICTION	1007	VOMITING
1007	NARCOTIC ABUSE	OPIATE ADDICTION	1007	GIDDINESS
1007	NARCOTIC ABUSE	OPIATE ADDICTION	1007	ITCHING AND BURNING
1008	PANIC ATTACKS	PANIC DISORDER	1008	ANXIETY
1008	PANIC ATTACKS	PANIC DISORDER	1008	DIZZINESS
1008	PANIC ATTACKS	PANIC DISORDER	1008	VOMITING
1008	PANIC ATTACKS	PANIC DISORDER	1008	GIDDINESS
1008	PANIC ATTACKS	PANIC DISORDER	1008	IRREGULAR HEART BEAT
1008	PANIC ATTACKS	PANIC DISORDER	1008	PAIN
1009	PEPTIC ULCER	PEPTIC ULCER	1009	RED COLORED VOMIT
1009	PEPTIC ULCER	PEPTIC ULCER	1009	BLACK COLORED STOOLS
1009	PEPTIC ULCER	PEPTIC ULCER	1009	WEIGHT LOSS
1009	PEPTIC ULCER	PEPTIC ULCER	1009	VOMITING
1009	PEPTIC ULCER	PEPTIC ULCER	1009	RED COLORED STOOLS
1009	PEPTIC ULCER	PEPTIC ULCER	1009	PAIN

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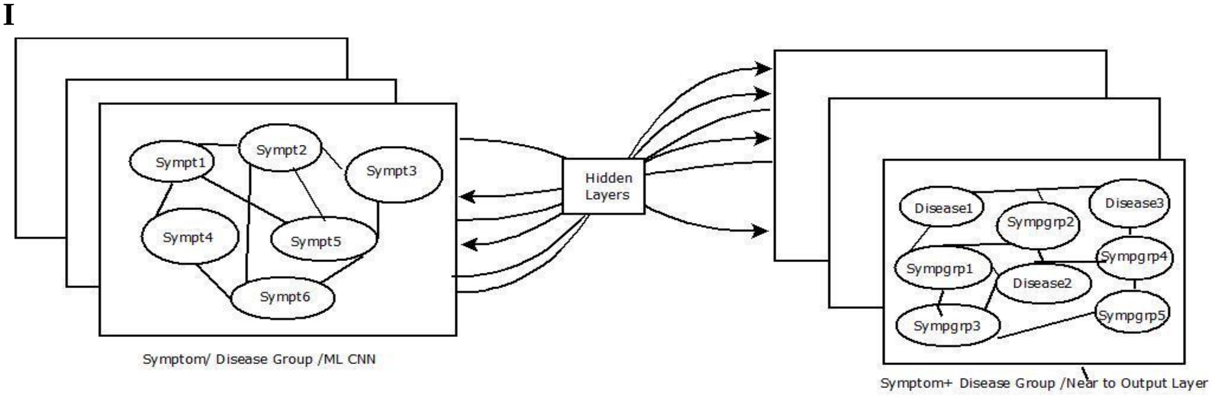
1010	IRON POISONING	IRON POISONING	1010	RED COLORED VOMIT
1010	IRON POISONING	IRON POISONING	1010	PAIN
1010	IRON POISONING	IRON POISONING	1010	DIARRHEA
1010	IRON POISONING	IRON POISONING	1010	BLACK COLORED STOOLS
1010	IRON POISONING	IRON POISONING	1010	RED COLORED STOOLS

I



4.4 Algorithm for Extended TGCN Classification

Step1: Start
Step2:Get Raw Data –RD (from questionnaires)
Step2.1: Declare TD-> Template Data Format,OD->Output Data
Step3: Convert CD(RD,TD)-OD
Step4:Declare ETGCNI as Input Layer
Step5:Input OD->ETGCNI->FLGNN (First Level GNN)
Step6:Process ETGNN(FLGNN,TPARAMETER)->TO
Step7:Process HL(TO)->OLD
Step8:Final Process OL(OLD)->Output
Step9:Output->Classified Data output
Step10:End / Stop

4.5 Performance and Accuracy Details

Algorithm	Accuracy	Disease Count	Execution Time
DTC	70%	40	21.07 ms

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NBC	100%	40	2243.79 ms
KNN	100%	40	1074.79 ms
AC	70%	40	2398.04 ms
RBC	70%	40	27.9091 ms
AE	90%	40	108.00 ms
DBM	100%	40	96.012 ms
DBN	100%	40	86.0335 ms
ETGN	100%	40	18.0255 ms

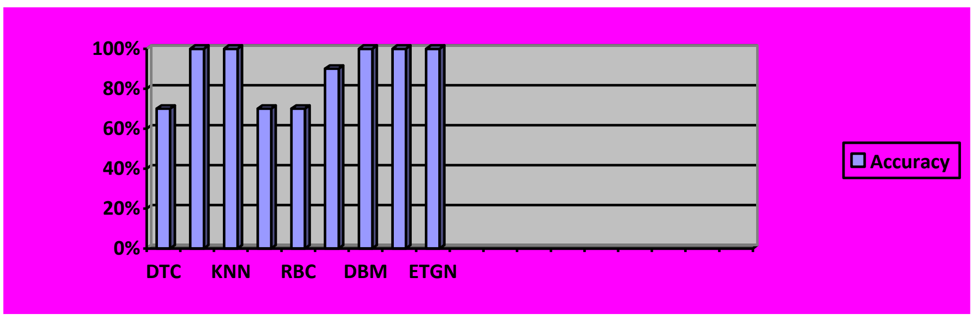

Figure 4 Algorithm Accuracy Comparison chart

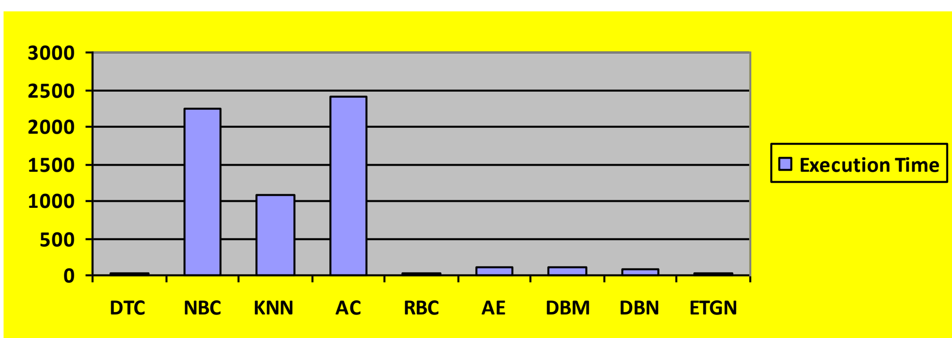

Figure 5 Algorithm Execution Time Comparison char

5. Conclusion

Thus, this paper provides complete solution for medical data classification with top most methods such as graph based convolution neural networks. In this paper there are many methods and existing works discussed, in detail. First Part explains about Convolution and Graph Neural

Network, Second Part Presents about data collection and data tables, Third part discuses about Recent Related Works such as RGCN, STGCN, AEGCN,DBN and more, followed by algorithm details , architecture diagram , performance comparison and accuracy details. Thus this research work may useful in Automated Clinical Support System or any Automated Medical Systems.

References

[1] [Aggarwal and Zhai 2012] Aggarwal, C. C., and Zhai, C. 2012. A survey of text classification algorithms. In *Mining text data*. Springer. 163–222.

[2] [Bastings et al. 2017] Bastings, J.; Titov, I.; Aziz, W.; Marcheggiani, D.; and Simaan, K. 2017. Graph convolutional encoders for syntax-aware neural machine translation. In *EMNLP*, 1957–1967.

[3] [Battaglia et al. 2018] Battaglia, P. W.; Hamrick, J. B.; Bapst, V.; Sanchez-Gonzalez, A.; Zambaldi, V.; Malinowski, M.; Tacchetti, A.; Raposo, D.; Santoro, A.; Faulkner, R.; et al. 2018. Relational inductive biases, deep learning, and graph networks. *arXiv preprint arXiv:1806.01261*.

[4] [Bruna et al. 2014] Bruna, J.; Zaremba, W.; Szlam, A.; and LeCun, Y. 2014. Spectral networks and locally connected networks on graphs. In *ICLR*.

[5] [Cai, Zheng, and Chang 2018] Cai, H.; Zheng, V. W.; and Chang, K. 2018. A comprehensive survey of graph embedding: problems, techniques and applications. *IEEE Transactions on Knowledge and Data Engineering* 30(9):1616– 1637.

[6] [Chen, Ma, and Xiao 2018] Chen, J.; Ma, T.; and Xiao, C. 2018. Fastgcn: Fast learning with graph convolutional networks via importance sampling. In *ICLR*.

[7] [Chenthamarakshan et al. 2011] Chenthamarakshan, V.; Melville, P.; Sindhwani, V.; and Lawrence, R. D. 2011.Concept labeling: Building text classifiers with minimal supervision. In *IJCAI*.

[8] [Conneau et al. 2017] Conneau, A.; Schwenk, H.; Barrault, L.; and Lecun, Y. 2017. Very deep convolutional networks for text classification. In *EACL*.

[9] [Defferrard, Bresson, and Vandergheynst 2016] Defferrard, M.; Bresson, X.; and Vandergheynst, P. 2016. Convolutional neural networks on graphs with fast localized spectral filtering. In *NIPS*, 3844–3852.

[10] [Hamilton, Ying, and Leskovec 2017] Hamilton, W.; Ying, Z.; and Leskovec, J. 2017. Inductive representation learning on large graphs. In *NIPS*, 1024–1034.

[11] [Henaff, Bruna, and LeCun 2015] Henaff, M.; Bruna, J.; and LeCun, Y. 2015. Deep convolutional networks on graphstructured data. *arXiv preprint arXiv:1506.05163*.

[12] [Hochreiter and Schmidhuber 1997] Hochreiter, S., and Schmidhuber, J. 1997. Long short-term memory. *Neural computation* 9(8):1735–1780.

[13] [Joulin et al. 2017] Joulin, A.; Grave, E.; Bojanowski, P.; and Mikolov, T. 2017. Bag of tricks for efficient text classification. In *EACL*, 427–431. Association for Computational Linguistics.

[14] [Kim 2014] Kim, Y. 2014. Convolutional neural networks for sentence classification. In *EMNLP*, 1746–1751.
[15] [Kingma and Ba 2015] Kingma, D., and Ba, J. 2015. Adam A method for stochastic optimization. In *ICLR*.
[16] [Kipf and Welling 2017] Kipf, T. N., and Welling, M. 2017. Semi-supervised classification with graph convolutional networks. In *ICLR*.
[17] [Le and Mikolov 2014] Le, Q., and Mikolov, T. 2014. Distributed representations of sentences and documents. In *ICML*, 1188–1196.
[18] [Li, Han, and Wu 2018] Li, Q.; Han, Z.; and Wu, X. 2018. Deeper insights into graph convolutional networks for semisupervised learning. In *AAAI*.
[19] [Li, Jin, and Luo 2018] Li, Y.; Jin, R.; and Luo, Y. 2018. Classifying relations in clinical narratives using segment graph convolutional and recurrent neural networks (seggcrns). *Journal of the American Medical Informatics Association* DOI: 10.1093/jamia/ocy157.
[20] [Liu, Qiu, and Huang 2016] Liu, P.; Qiu, X.; and Huang, X. 2016. Recurrent neural network for text classification with multi-task learning. In *IJCAI*, 2873–2879. AAAI Press.
[21] [Luo et al. 2014] Luo, Y.; Sohani, A. R.; Hochberg, E. P.; and Szolovits, P. 2014. Automatic lymphoma classification with sentence subgraph mining from pathology reports. *Journal of the American Medical Informatics Association* 21(5):824–832.
[22] [Luo et al. 2015] Luo, Y.; Xin, Y.; Hochberg, E.; Joshi, R.; Uzuner, O.; and Szolovits, P. 2015. Subgraph augmented non-negative tensor factorization (santf) for modeling clinical narrative text. *Journal of the American Medical Informatics Association* 22(5):1009–1019.