THE IIOAB JOURNAL

VOLUME 10 : NO 1 : APRIL 2019 : ISSN 0976-3104

Institute of Integrative Omics and Applied Biotechnology Journal

Dear Esteemed Readers, Authors, and Colleagues,

I hope this letter finds you in good health and high spirits. It is my distinct pleasure to address you as the Editor-in-Chief of Integrative Omics and Applied Biotechnology (IIOAB) Journal, a multidisciplinary scientific journal that has always placed a profound emphasis on nurturing the involvement of young scientists and championing the significance of an interdisciplinary approach.

At Integrative Omics and Applied Biotechnology (IIOAB) Journal, we firmly believe in the transformative power of science and innovation, and we recognize that it is the vigor and enthusiasm of young minds that often drive the most groundbreaking discoveries. We actively encourage students, early-career researchers, and scientists to submit their work and engage in meaningful discourse within the pages of our journal. We take pride in providing a platform for these emerging researchers to share their novel ideas and findings with the broader scientific community.

In today's rapidly evolving scientific landscape, it is increasingly evident that the challenges we face require a collaborative and interdisciplinary approach. The most complex problems demand a diverse set of perspectives and expertise. Integrative Omics and Applied Biotechnology (IIOAB) Journal has consistently promoted and celebrated this multidisciplinary ethos. We believe that by crossing traditional disciplinary boundaries, we can unlock new avenues for discovery, innovation, and progress. This philosophy has been at the heart of our journal's mission, and we remain dedicated to publishing research that exemplifies the power of interdisciplinary collaboration.

Our journal continues to serve as a hub for knowledge exchange, providing a platform for researchers from various fields to come together and share their insights, experiences, and research outcomes. The collaborative spirit within our community is truly inspiring, and I am immensely proud of the role that IIOAB journal plays in fostering such partnerships.

As we move forward, I encourage each and every one of you to continue supporting our mission. Whether you are a seasoned researcher, a young scientist embarking on your career, or a reader with a thirst for knowledge, your involvement in our journal is invaluable. By working together and embracing interdisciplinary perspectives, we can address the most pressing challenges facing humanity, from climate change and public health to technological advancements and social issues.

I would like to extend my gratitude to our authors, reviewers, editorial board members, and readers for their unwavering support. Your dedication is what makes IIOAB Journal the thriving scientific community it is today. Together, we will continue to explore the frontiers of knowledge and pioneer new approaches to solving the world's most complex problems.

Thank you for being a part of our journey, and for your commitment to advancing science through the pages of IIOAB Journal.

Yours sincerely,

Vasco Azevedo

***Vasco Azevedo**, Editor-in-Chief*
Integrative Omics and Applied Biotechnology
(IIOAB) Journal

REGULAR ISSUE

ARTICLE

DBKE-3NC: A DISTRIBUTED NEAREST-NEIGHBOUR NORMALIZATION ALGORITHM FOR DISTRIBUTED DATA MINING UNDER PRIVACY CONSTRAINTS

S. Urmela*, M. Nandhini

Department of Computer Science, Pondicherry University, INDIA

ISSN 0976-3104

ABSTRACT

Background: *To propose an architecture for DDM using Nearest Neighbour Normalization under privacy constraints for Electronic Health Records (EHRs) and Agriculture Weather Forecast.* ***Methods:*** *This paper proposed two algorithms are proposed: Nearest Neighbour Normalization with correlation (3NC) algorithm to normalize the raw data in local level (distributed datasite) and Double Blind Key-attribute based Encryption (DBKE) algorithm to deploy the protection of data in both local and global (central site) levels.* ***Results:*** *The proposed 3NC algorithm aims to maximize the accuracy and minimize the error rate by lossless and predicted normalization technique on understanding the data distribution in local levels. The proposed DBKE algorithm aims to maximize the confidential level and accuracy by efficient privacy technique. Further, proposed architecture aims to minimize the computational complexity and memory overhead by maintaining the history of records clusters and retrieving required clusters by proposed recall grading algorithm.* ***Conclusions:*** *Experimental implementation on EHRs and Agriculture Weather Forecast depicts an improved performance compared to other state-of-arts heterogeneous-distributed retrieval approaches.*

KEY WORDS
Distributed Data Mining, heterogeneous datasites, data normalization, privacy-preserving, Electronic Health Records, Agriculture Weather Forecast

INTRODUCTION

Reduction in storage cost and due to enormous growth of technologies has led to emergence of distributed systems. Most of the commercial off-the-shelf components are designed to work on centralized location. This centralized approach doesn't work well in recent distributed environments due to computation and storage constraints. Recent data mining involves database in which data is stored in one geographical location. Future data mining tasks works on data stored in different geographical location called Distributed Data Mining (DDM). The ultimate goal is to mine data which is distributed in homogeneous and heterogeneous sites [1].

Data located at local level is first mined with suitable DM algorithm and all the computed data from local level is agglomerated to form global level prediction. There are two-variations in this case, computation done at local level and data stored at global level [Fig. 1(a)], data stored at local level and computation done at global level [Fig. 1(b)]. A special variation of DDM, in which both data and computation is done at local level [2][Fig. 1(c)]. In proposed work, data and computation is stored both in local and global levels [Fig. 1(d)].

Alfredo Cuzzocrea (2013)[3] stated that framing a framework/methodology for DDM is challenging not only by distributed environment, but also for its minimized computational complexity and efficient storage of data in local and global levels. Centralized data mining algorithms/systems designed for centralized systems cant' be applied for distributed environment. Fu Y et al. (2012)[4] discussed certain key characteristics in designing DDM algorithms: minimizing space and computation complexity, designing suitable algorithm for both homogeneous and heterogeneous datasets and maintaining local datasets independence. Further, all these issues are interrelated to each other. This has set way to many researchers to carry-out their work in this field. The main contributions of proposed work are summarized as follows:

Received: 18 Sep 2018
Accepted: 30 Nov 2018
Published: 02 Jan 2019

- Proposing an effective privacy-preserving distributed mining algorithm based on Double-Blind Key Attribute based Encryption algorithm with Nearest Neighbour Normalization-Correlation which successfully utilizes the distributed environment.
- Proposing an effective heterogeneous distributed mining technique which maintains universal dataset across distributed datasites.
- Design and evaluation of proposed mining technique on Electronic Health Records (EHRs) and Agriculture Weather Forecast dataset for resolving data disclosure and for predicting dynamic updations in distributed environment.
- Measuring the metrics such as effectiveness, efficiency, privacy-technique evaluation and normalization technique evaluation metrics on proposed technique.

The proposed architecture in this paper involves records retrieved by Nearest Neighbour Normalization-Correlation (3NC) technique with Double-Blind Key Attribute based Encryption algorithm (DBKE). At local level, distributed data stored in multi-linked list is privacy preserved by DBKE algorithm. DBKE algorithm prevents key-attribute data disclosure to neigbouring local levels and global level by encrypting the data with double-blinded function (symmetric encryption function and hashing function). At global level, encrypted key-attribute in decrypted by reverse encryption (unhashing function and symmetric decryption function). This privacy algorithm is for preventing data disclosure during storage in local levels. The key-attribute is used for classifying records. 3NC technique uses MAX and MIN value of key-attribute for

*Corresponding Author
Email: urmelaindra@gmail.com

IIOAB JOURNAL
ISSN: 0976-3104

forming dendrogram. Say, for classifying a patient diagnosed with corresponding disease or not. Initially, the prime key-attribute is used for classifying on analyzing the MAX and MIN value. From the clusters formed, MAX value is normalized to highest value in corresponding cluster. Then by correlation, secondary key-attribute is used for further classifying patients diagnosed with particular disease or not. From the sub-clusters formed, MAX value is normalized to highest value in corresponding sub-cluster. Each branch of dendrogram corresponds to a cluster (sub-cluster). The clusters formed are migrated to global level for final result prediction.

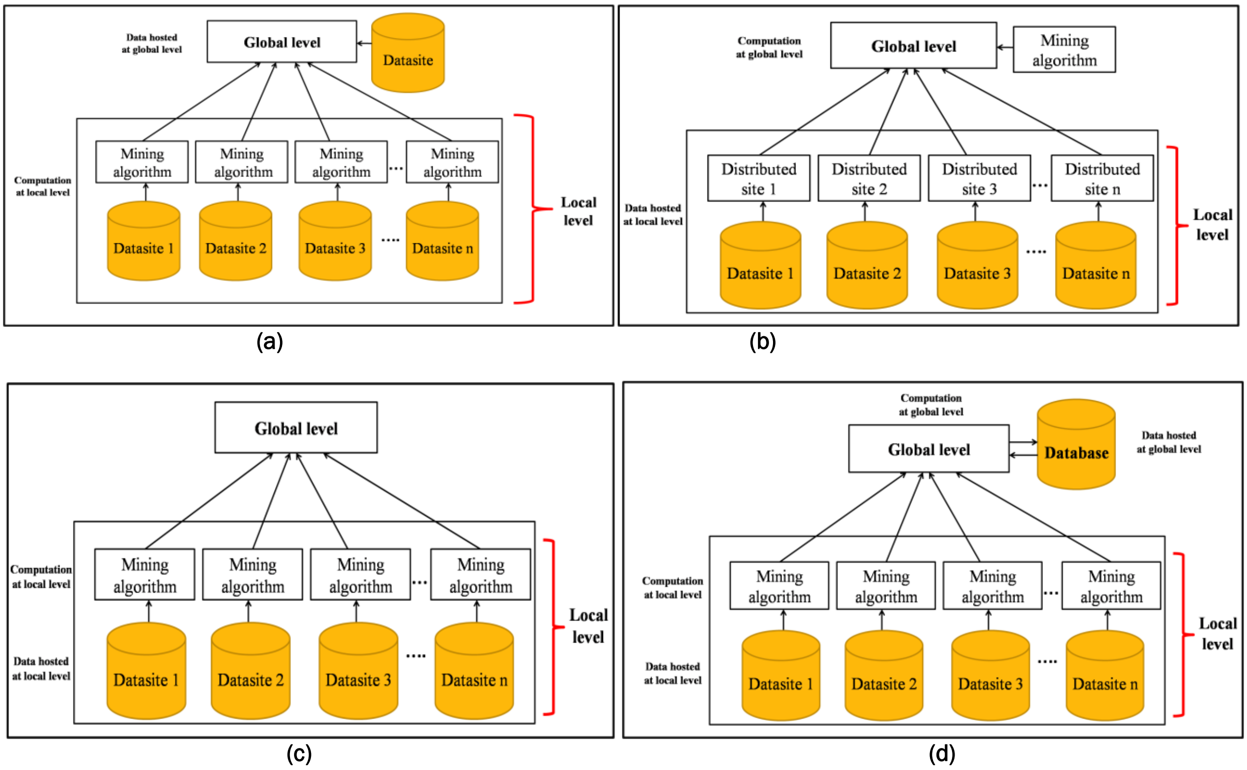


Fig. 1: Working architecture – DDM (a) data hosted at global level, computation at local level (b) data hosted at local level, computation at global level (c) both data hosting and computation in local level (d) data hosting and computation in both local and global levels.

At global level, old clusters migrated from local levels assigned grades by proposed recall grading algorithm. The number of clusters formulated for each disease in local levels (on-the-fly) and stored in global level (old records) must be equal. Clusters communicated to global level were assigned grades by recall grading algorithm. Finally, both cluster sets retrieved from local levels and records stored in global level (old records) sums up their grades and their average value is again assigned final grades. Proposed architecture is implemented on real-world openly available datasets taken from UCI data repository.

The organization of paper is as follows: Section 2 discusses EHRs and Agriculture weather forecast dataset description. Section 3 depicts proposed architecture for effective retrieval of records in distributed environment. Section 4 presents performance analysis and result discussion of proposed architecture. Section 5 summarizes the paper.

DATASET DESCRIPTION

EHRs and Agriculture Weather Forecast are the datasets considered for evaluation of proposed architecture. Dataset description of both the datasets is discussed here.

Case study 1: Electronic Health Records (EHRs)

EHRs are becoming worldwide popular way of maintaining health records of a person. The difference between EHR and Patient Health Record(PHR) is that PHR includes medical record for only a particular disease diagnosed for a person (for a short time period say, 3 years) whereas EHR includes medical record of a person right from their birth till death (for lifetime)[5]. EHR includes person therapeutic history, drug usage, allergies and test outcomes. It is supported by EHR management and decision support [6]. In DDM, EHRs are utilized and updated in either homogeneously/heterogeneously distributed data sites.

Case study 2: Agriculture Weather-Forecast

Agriculture database uses information collected from different geographical location in periodical manner. Details relating to crop plantation and weather monitored data collected from heterogeneous data sites

IIOAB JOURNAL
ISSN: 0976-3104

are maintained in a universal database. This profile includes plantation details, weather details relating to heterogeneous sites. This data is used for giving efficient and timely farming details to farmers. [7]

Analysis of case studies

Both the case studies considered are analyzed on different parameters as shown in [Table 1] stakeholders, expert systems used, local and global level DDM users, no. of local levels considered for evaluation of proposed algorithm, profiles of case study with commonality, common attributes and key attributes of applications used for formulating dendrogram.

Table 1: Comparison of case study 1: EHRs and case study 2: Agriculture weather forecast

Parameters	Electronic Health Records (EHRs)	Agriculture Weather Forecast
Stakeholders	Health care providers (doctors, nurses, etc)	Weather forecaster, Agriculture specialist
	Patients	Agriculturist
	Health experts	Weather and Agriculture experts
Expert systems	EHR management and decision support	Weather Forecast record management and decision support
DDM-Local level users	Health care personnel	Agriculturist personnel
DDM-Global level users	Health care personnel/other government personnel related to Health	Weather forecaster and agriculture specialist Personnel
No. of local levels	7	7
Profiles	Demographic profile	Demographic profile
	Anthropometric profile	Soil profile
	Clinical results profile	Weather profile
	Medication/allergies vaccination profile	Plantation profile
Common attributes	Patient Name Age Address Gender Location	Farmer Name Age Address Gender Location
Key-attributes	Hypertension: SBP DBP Age Diabetes: GlyHb (Glycalated Hemoglobin) Age	Agriculture Weather Forecast: Relative_temperature Humidity Wind Speed Age
Functionality	Adding new EHR record at local level	Adding new farmer record at local level
	Updating existing EHR record at local level	Updating existing farmer record at local level
	Deleting EHR record at local level	Deleting farmer record at local level
	Filtering EHR record based on user query at global level	Filtering farmer record based on user query at global level
	Dendrogram formulation with EHRs at local level based on user query	Dendrogram formulation with farmer records at local level based on user query

DESIGN OF PROPOSED ARCHITECTURE

Proposed architecture working is classified at two-levels: local and global levels. At local level records undergo proposed two stages namely,

STAGE I: Data Mining (Nearest Neighbour Normalization-Correlation algorithm)
STAGE II: Privacy-preserving of local and global data (Double-Blind Key-attribute based Encryption algorithm)

At global level records undergo proposed two stages namely,

STAGE I: Recall-grading algorithm
STAGE II: Filtering final cluster set

STAGE I: Data Mining (Nearest Neighbour Normalization-Correlation algorithm)

IIOAB JOURNAL ISSN: 0976-3104

Filling missing values

In proposed architecture, at local levels the data structure used for storage of data is multi-linked list. Consider EHRs dataset, the data storage at local level is depicted in fig. 2. At each local level, the missing values are filled from the relative data of corresponding entity. For any type application, there are two types of filling missing values. Filling demographic data and filling application-specific data[8]. Demographic data includes filling general information. Example: filling entity age from DOB, etc. Application-specific data includes filling application-oriented data8. For medical dataset, clinical results of patient are filled by relative computation of corresponding data. For example, say in hypertension dataset if the value of SBP (Systolic Blood Pressure)/DBP (Diastolic Blood Pressure) for a continuous range is 148/78, 140/79, 152/73 then the next value is computed as relative mean (147/77)[9].

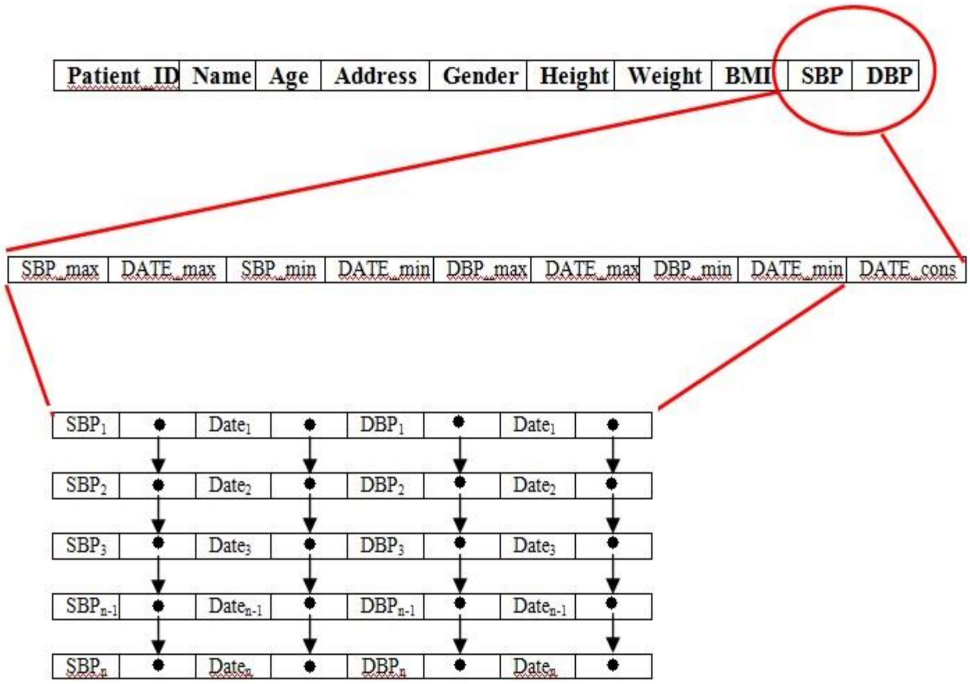


Fig. 2: Data Structure representation

……………………………………………………………………………………….

Say, for a patient at each local level, if SBP/DBP value is monitored daily, it leads to huge volume of data values. To overcome the problem of maintaining history of records, for every 20 data values of SBP and DBP database is consolidated. MAX and MIN value of SBP and DBP among the old 20 records along with time recorded of MAX and MIN values and the time data was consolidated is noted. In next sub-stage, key attributes (SBP and DBP) is normalized. Key-attributes are sensitive attributes used for classifying patients diagnosed with disease or not which needs to be privacy preserved. In this proposed architecture, SBP and DBP values are used for classifying a patient as hypertension or not.

Dendrogram formulation by Nearest Neighbour Normalization-Correlation (3NC)

From the clinical data, MAX and MIN values of key-attributes are calculated using which clusters are formulated for mining. For example if SBP value for a single entity reading is 120,134,115,132,134,121,117,128 then MAX = 134 and MIN = 115. Similarly DBP value reading is 80,79,83,82,82,84,82,80 then MAX = 84 and MIN = 79. ICD-9 code (International statistical code for Classification of Diseases)[10] is used as a standard reference for classifying patients diagnosed with disease.

Consider the case of classifying patient diagnosed with hypertension disease. There are two-levels involved in formulating dendrogram. At first level, the dendrogram is formulated with SBP values as shown in fig. 3. According to ICD-9 code, the range of classifying SBP is <=120, 121-140,141-160,161-180,181-200 and >200 on analyzing the (MAX,MIN) pair. From the fig. 3 on first level classification clusters are formed say C1 to C24 with defined range. In C1, patients (P1-P10) fall under category with SBP <=120. From the (MAX,MIN) pair of 10 patients, all 10 MAX value is normalized to largest MAX value in corresponding cluster. Likewise for all 24 clusters, same normalization technique is followed.

At second level, from the normalized clusters second level of classifying patients with DBP is done. According to ICD-9 code, the range of classifying DBP is <=80, 81-100,101-120, >120 on analyzing the (MAX,MIN) pair. The way of classifying records in two-way as discussed above is called correlation. Correlation among two variables means they are interdependent on each other. For diagnosing a patient with hypertension, both SBP and DBP values are monitored. Hence the algorithm proposed is called 3NC

IIOAB JOURNAL
ISSN: 0976-3104

algorithm. From the [Fig. 3] on second level classification sub-clusters with defined range of DBP is formed. In C11, patients (P2, P5 and P6) fall under category with DBP <=80. From the (MAX,MIN) pair of those three patients, all three MAX value is normalized to largest MAX value of DBP in corresponding cluster. Likewise for all sub-clusters, same normalization technique is followed. According to the example in [Fig. 3], 96 sub-clusters are formed by 3NC which in-depth classifies patients with hypertension disease.

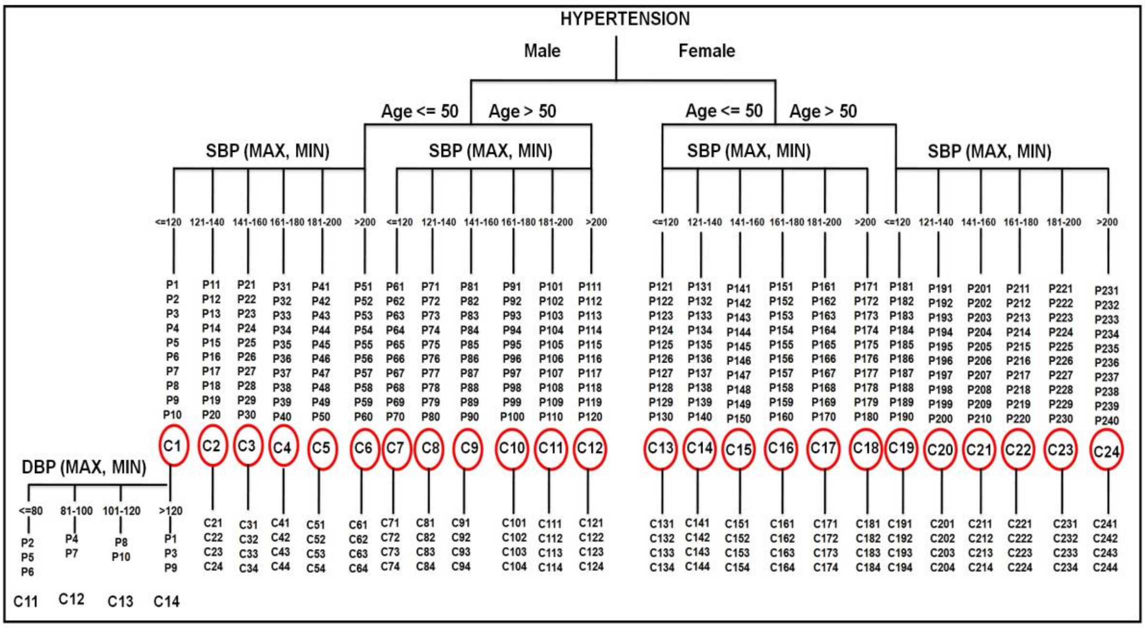


Fig. 3: Dendrogram formulation - Nearest Neighbour Normalization-Correlation

[Fig. 3] depicts correlation and normalization on EHRs for a single cluster C1 retrieved from dendrogram. Initially cluster set is retrieved on analyzing the (MAX,MIN) pair of SBP value. After forming cluster with SBP value, MAX value is normalized for all the clusters formed. Then DBP value is analyzed which forms sub-cluster with (MAX,MIN) pair of DBP value. Consider for C1, four sub-clusters are formed. Sub-clusters formed for C1 are C11,C12,C13,C14. After sub-clusters formation with SBP and DBP, MAX value of DBP in each cluster is normalized with highest MAX value of corresponding cluster set.

STAGE II: Privacy-preserving of local data (Double-Blind Key-attribute based Encryption algorithm)

The calculated (MAX,MIN) pair is highly-sensitive data which needs to be protected and kept confidential at local level and during migration of data from local level to global level for resultant query. The value of (MAX,MIN) pair of key attribute is used for mining. The proposed Double-Blind Key-attribute based Encryption (DBKE) algorithm at each local level employs an encryption function followed by hashing function. The key used for encryption function and hashing function of each local level is stored as a secret share between each heterogeneous distributed local and global level.

Blind function is a service provided to client which computes function for encrypting the data without revealing the original data [11]. In proposed algorithm, Double-Blind technique is followed which computes two encryption functions at local level and two decryption functions at global level to protect sensitive key-attribute data.

Processing at local level

The (MAX,MIN) pair computed data of key-attribute is twice privacy-preserved with an encryption function and a hashing function.

Encryption function by symmetric encryption key

At first level, the (MAX,MIN) value of key-attribute is encrypted using symmetric encryption key.
The encryption function is computed as,
Encrypted data, E1 = E (K,I)

Encrypted data, E1 = E (K,(MAX,MIN))
where I - input data (MAX,MIN) and K - key value for encryption.
Hashing function by key-value

IIOAB JOURNAL
ISSN: 0976-3104

At second level, hashing function is applied to the encrypted data, which computes hashing function individually for MAX and MIN of key-attribute.
Hash function, F(E1) = E1 MOD N
where E1 – Encrypted data and N – key value for encryption.

Processing at global level

The Double-Blind encrypted (MAX,MIN) pair migrated from local level is decrypted in reverse. At first level, unhashing function (Reverse decryption) is applied on double-blind encrypted (MAX,MIN) data.

Unhashing function by reverse decryption

On knowing the N, key value used in hashing function, reverse decryption process is possible which computes the MAX and MIN value individually. The output of unhashing function is D1.

Decryption function by symmetric decryption key

At second level, decryption function is applied on the single-decrypted (MAX,MIN) data to obtain the original (MAX,MIN) pair.
The decryption function,
Input data, I = D (D1,K)
where, K – key value used for encryption at local level, D1 – single-level decryption output (Unhashing function).

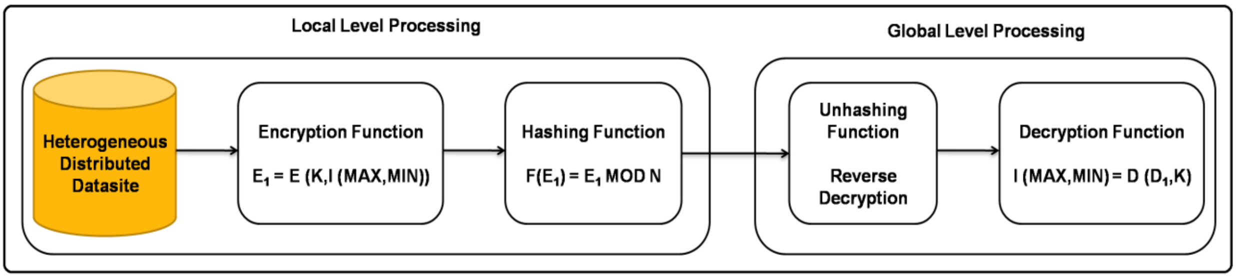


Fig. 4: Double-Blind Key-attribute based Encryption algorithm

STAGE I: Recall-Grading Algorithm

At global level, record clusters retrieved by 3NC algorithm undergoes proposed recall-grading algorithm. Some clusters (old records) would be retrieved earlier by 3NC algorithm. With those clusters a matrix is formulated with clusters say, C11, C21, etc and user-query Q1, Q2, etc. A ✓(tick mark) indicates including the corresponding clusters in user-query and X (cross mark) indicates excluding the corresponding clusters in user-query. Only those records which are updated in local level or new records corresponding to user query, undergoes 3NC algorithm and clusters are transferred from local level to global level. Based on proposed recall-grading algorithm, grades are assigned for each corresponding clusters (from same dendrogram branch) based on recall metric.

Recall-grading algorithm for each cluster takes on by calculating recall metric of each records of individual clusters. The calculated recall metric of each cluster is obtained by taking an average of summing individual records recall metric. Grades are assigned to calculated recall metric. Higher recall value were assigned higher grades.
Each record cluster transferred from local levels to global level is considered. Recall metrics of individual records of each cluster is calculated. Recall metric of cluster is summation of recall metric of individual records and taking an average. Finally, grades are assigned to individual cluster. Higher grades being assigned to higher recall metric clusters. Higher grades cluster corresponds to relevant records corresponding to user query Q.

STAGE II: Filtering final cluster set

Record cluster sets of old records and new records along with their grades are finally consolidated by taking an average of both grades. Architecture of proposed DBKE-3NC, distributed Nearest-Neighbour Normalization algorithm for DDM under privacy constraints is shown in [Fig. 5].

EXPERIMENTAL IMPLEMENTATION

The experiment is carried out on a single 64-bit machine, windows 7 OS having 3GHz Intel dual core processor with 4GB main memory. The proposed algorithm is coded in C# and implemented in HDFS

(Hadoop Distributed File System) distributed environment. The proposed architecture is implemented with seven distributed local levels both for EHRs and Agriculture Weather Forecast dataset. Seven local levels are created with a server at global level. Comparative analyses have been carried out with performance evaluation metrics of proposed architecture with conventional approaches. The proposed architecture is implemented on openly-available real-world EHRs and Agriculture Weather Forecast obtained from UCI repository [12].

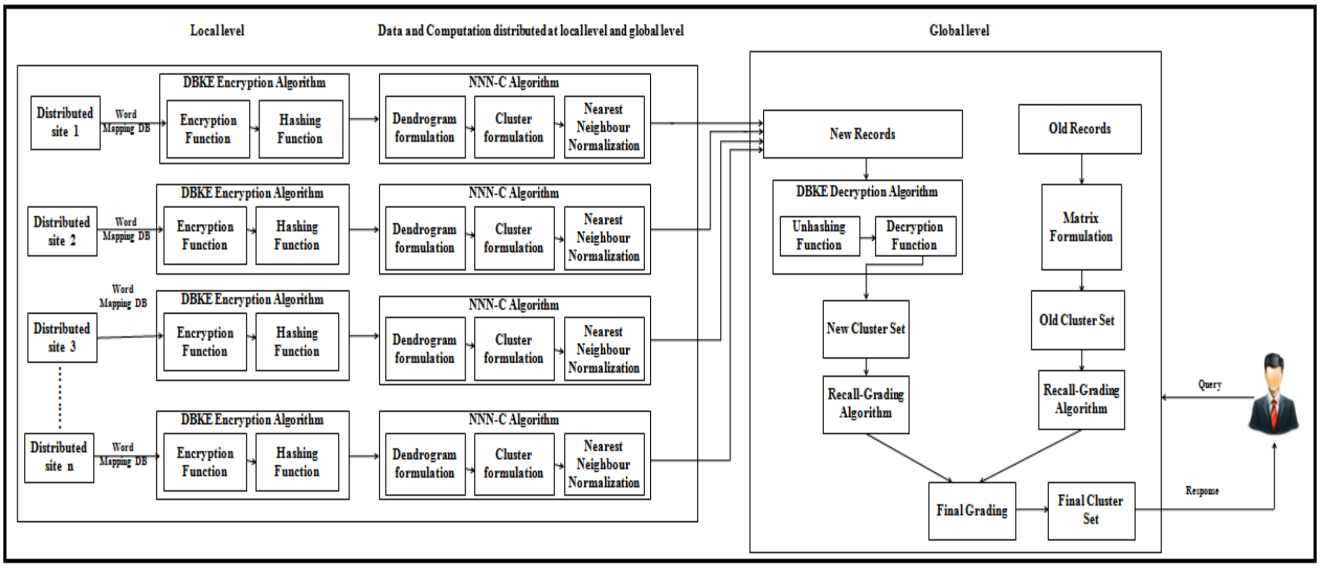


Fig. 5: Proposed Architecture - DBKE-3NC: distributed Nearest-Neighbour Normalization algorithm for Distributed Data Mining under privacy constraints.

....

Effectiveness metrics

This measure is computed in terms of retrieving successful result meeting user query. Effectiveness measures include precision[13], recall[14], F-measure[15] and result accuracy[16].

Table 2: Effectiveness measures Vs Heterogeneous classifier approaches

Dataset	Metrics (%)	Collective Decision Tree	Distributed Clustering	Collective Bayesian Learning	Collective Principal Component Analysis	Proposed DendrogramCluster formulation
EHRs	Precision	0.6942	0.9218	0.9012	0.9045	0.9434
	Recall	0.6571	0.9202	0.8449	0.8756	0.9023
	F-measure	0.6751	0.9103	0.8721	0.8937	0.9224
Agriculture Weather Forecast	Precision	0.6582	0.9190	0.8390	0.8759	0.9381
	Recall	0.6337	0.8681	0.8054	0.8571	0.9010
	F-measure	0.6482	0.8976	0.8189	0.8668	0.9218

[Table 2] depicts precision, recall and F-measure comparison of proposed mining algorithm with the state-of-art mining techniques. Collective Principal Component Analysis (P-90.45%, R-87.56% for EHRs and P-87.59% R-85.71% for Agriculture Weather Forecast) exhibits more compared to former two techniques because dynamic updations of records from individual local levels are considered but lesser compared to proposed dendrogram cluster formulation technique (P-94.34% R-90.23% for EHRs and P-93.81% R-90.1% for Agriculture Weather Forecast) because repetitive records are considered which needs to be eliminated leading to decreased retrieval rate. Collective Bayesian learning exhibits more values (P-90.12% R-84.49% for EHRs and 83.9% R-80.54% for Agriculture Weather Forecast) compared to Collective decision tree exhibits (P-69.42% R-65.71% for EHRs and 65.82% R-63.37% for Agriculture Weather Forecast) because in bayesian learning technique on-the-fly or updated records are considered for mining whereas in distributed clustering updated records are considered. Distributed clustering exhibits higher values (P-92.18% R-90.02% for EHRs and P-91.9% R-86.81% for Agriculture Weather Forecast) compared to all the techniques because dynamic records are considered for mining leading to effective retrieval rate but less than proposed because of mismatch of key-attributes of each local level.

IIOAB JOURNAL ISSN: 0976-3104

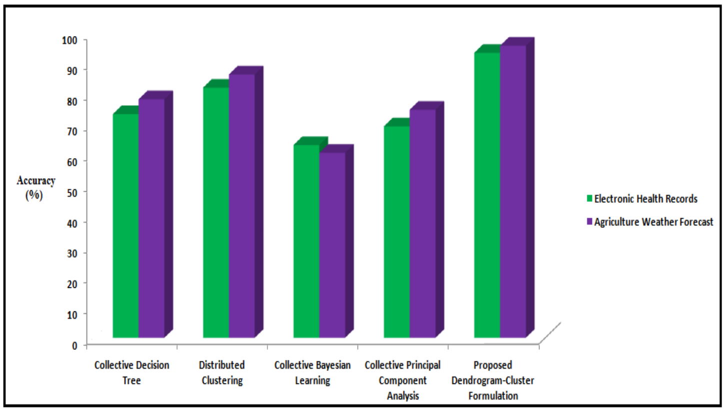
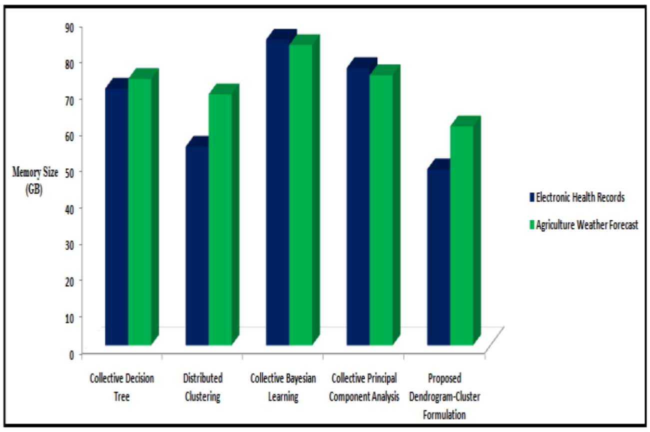


Fig. 6: Accuracy Vs Heterogeneous classifier approaches.

[Fig. 6] depicts accuracy comparison of proposed mining algorithm with the state-of-art mining techniques. Proposed dendrogram cluster formulation technique exhibits more accuracy (93.56% for EHRs and 95.89% for Agriculture Weather Forecast) compared to former four techniques because updated records from local levels is considered and redundant records are cross-checked. Distributed clustering (82.14% for EHRs and 86.47% for Agriculture Weather Forecast) exhibits more accuracy compared to collective Principal Component Analysis (69.41% for EHRs and 74.87% for Agriculture Weather Forecast), collective Bayesian learning (63.28% for EHRs and 60.72% for Agriculture Weather Forecast) and collective decision tree (73.4% for EHRs and 78.29% for Agriculture Weather Forecast) because of two-level of dendrogram formulation leading to sub-cluster formulation which increases the result accuracy

Efficiency metrics

This measure is computed in terms of retrieving effective result on varying environment. Efficiency measures include execution time [17] and memory cost [18].



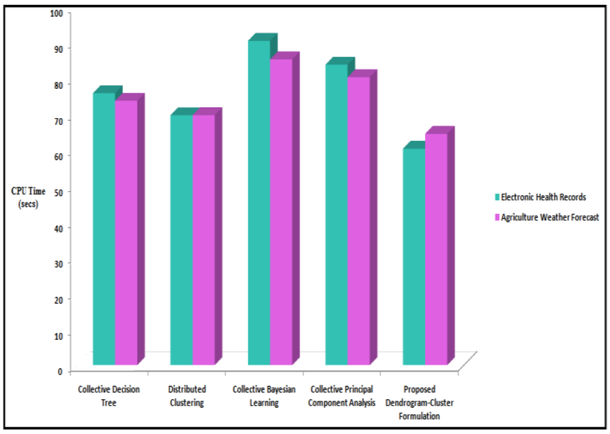


Fig. 7: (a) Memory Size Vs Heterogeneous classifier approaches (b) Execution Time Vs Heterogeneous classifier approaches.

[Fig. 7] depicts memory size comparison of proposed mining algorithm with the state-of-art mining techniques. Proposed dendrogram cluster formulation technique exhibits less memory cost (48.54% for EHRs and 60.39% for Agriculture Weather Forecast) compared to former four techniques because old key-attribute values are consolidated for every 20 values and by normalization technique data values are minimized leading to less memory cost. Distributed clustering exhibits less memory size (54.78% for EHRs and 69.25% for Agriculture Weather Forecast) compared to collective Principal Component Analysis (76.48% for EHRs and 74.52% for Agriculture Weather Forecast) collective Bayesian learning (84.34% for EHRs and 82.83% for Agriculture Weather Forecast) collective decision tree (70.81% for EHRs and 73.48% for Agriculture Weather Forecast) because by clustering technique old records are stored in global level and only new records are migrated from local level to global level for

[Fig. 7] depicts execution time comparison of proposed mining algorithm with the state-of-art mining techniques. Proposed dendrogram cluster formulation technique exhibits less execution time (60.43% for EHRs and 64.6% for Agriculture Weather Forecast) compared to former four techniques because by two-level dendrogram and sub-cluster formation time taken to retrieve records corresponding to user query is reduced. Further, by word-mapping database at global level for identifying the key-attribute to be

IIOAB JOURNAL
ISSN: 0976-3104

considered at each local level for mining reduces the time taken for mining process. Distributed clustering (69.78% for EHRs and 69.81% for Agriculture Weather Forecast) exhibits less execution time compared to other three techniques, (collective Principal Component Analysis (83.89% for EHRs and 80.41% for Agriculture Weather Forecast) collective Bayesian learning (90.54% for EHRs and 85.39% for Agriculture Weather Forecast) collective decision tree (75.92% for EHRs and 73.81% for Agriculture Weather Forecast)) because clustering technique retrieves old key-attribute entries and new key-attribute entries are retrieved for every updations.

Privacy technique evaluation metrics

Performance of proposed privacy-preserving algorithm is analyzed on two measures: accuracy and confidence level [19].

Table 3: Privacy evaluation metrics Vs Privacy techniques

Dataset	Metrics (%)	Additive Noise Addition	Multiplicative Noise Addition	L-Diversity	T-Closeness	DBKE Algorithm
EHRs	Accuracy	98.23	99.32	97.14	96.73	99.38
	Confidence Level	94.37	96.21	98.37	99.42	99.40
Agriculture Weather Forecast	Accuracy	97.59	98.37	96.32	97.02	99.04
	Confidence level	94.89	95.92	97.58	98.74	98.91

[Table 3] depicts accuracy comparison of proposed DBKE algorithm with the state-of-art privacy preserving approaches. Proposed DBKE algorithm exhibits more accuracy (99.38% for EHRs and 99.04% for Agriculture Weather Forecast) compared to other randomization and anonymization approaches because of combining both randomization and anonymization approach. Randomization approaches, additive noise addition (98.23% for EHRs and for 97.59% Agriculture Weather Forecast) and multiplicative noise addition (99.32% for EHRs and 98.37% for Agriculture Weather Forecast) exhibits more accuracy value but privacy/confidence level is less because original data can be retrieved on analyzing the spectral values of randomized data. Anonymization approaches, L-Diversity (97.14% for EHRs and 96.32% for Agriculture Weather Forecast) and T-Closeness (96.73% for EHRs and 97.02% for Agriculture Weather Forecast) exhibits less accuracy compared to randomization approaches but confidence/privacy level is more than randomization approaches. In conventional approaches there is some data loss incurred while converting the original data to protected data.

[Table 3] depicts confidence level comparison of proposed DBKE algorithm with the state-of-art privacy preserving approaches. Proposed algorithm exhibits more confidence level (99.40% for EHRs and 98.91% for Agriculture Weather Forecast) compared to randomization and anonymization approaches because the distribution of original data is considered in proposed DBKE algorithm. Randomization approaches, additive noise addition (94.37% for EHRs and 94.89% for Agriculture Weather Forecast) and multiplicative noise addition (96.21% for EHRs and 95.92% for Agriculture Weather Forecast) exhibits less confidence level compared to anonymization approaches and proposed DBKE algorithm. Similarly, anonymization approaches, L-Diversity (98.37% for EHRs and 97.58% for Agriculture Weather Forecast) and T-Closeness (99.42% for EHRs and 98.74% for Agriculture Weather Forecast) exhibits higher or equal confidence level compared to proposed DBKE algorithm but result accuracy is less. In conventional approaches data distribution at each local datasite and global level is not considered while converting the original data to protected data.

Normalization technique evaluation metrics

Performance of proposed normalization algorithm is analyzed on two measures: MSE and RMSE [20].

Table 4: Normalization evaluation metrics Vs Normalization techniques

Dataset	Metrics (%)	Min-max normalized data	z-score normalized data	Decimal scaling normalized data	3N without C normalized data	3NC normalized data
EHRs	MSE	1.2313	1.3621	1.1182	0.9045	0.1972
	RMSE	1.1782	1.1892	1.2781	0.9510	0.3958
Agriculture Weather Forecast	MSE	1.4431	1.5467	1.1576	1.7345	0.2056
	RMSE	1.2012	1.2437	1.0760	1.3171	0.4534

Table 4 depicts MSE and RMSE comparison of proposed 3NC algorithm with the state-of-art normalization techniques. Min-max exhibits less MSE and RMSE (1.2313, 1.1782 for EHRs and 1.4431, 1.2012 for Agriculture Weather Forecast) compared to z-score (1.3621, 1.1892 for EHRs and 1.5467, 1.2437 for Agriculture Weather Forecast) because out-of-bound error is triggered in min-max normalization when the normalized range doesn't fall within the specified range. In decimal scaling MSE and RMSE (1.1182, 1.2781 for EHRs and 1.1576, 1.0760 for Agriculture Weather Forecast) error rate is less compared to former two normalization techniques because prior knowledge of max and min value of normalized attribute is known. 3N without C algorithm (0.9045, 0.9510 for EHRs and 1.7345, 1.3171 for Agriculture Weather Forecast) exhibits more error rate compared to proposed 3NC because data distribution is not considered leading to less accuracy rate. Proposed 3NC algorithm (0.1972, 0.3958 for EHRs and 0.2056, 0.4534 for Agriculture Weather Forecast) exhibits better performance than former three state-of-art normalization techniques because data distribution at local levels is considered minimizing the error rate. Proposed 3NC algorithm considers all the data within specified range and outlier values for normalization.

CONCLUSION

In recent years, DDM evolved in large aiming for efficient and timeliness data retrieval. Many proposed works framed model for partial DDM, rather utilizing distributed data and computation. In this paper, a distributed Nearest-Neighbour Normalization algorithm for DDM under privacy constraints is proposed with dynamic distributed datasets, EHRs and Agriculture Weather Forecast. In this model, algorithms for normalization and privacy are proposed. By normalization-correlation technique, two-level dendrograms and sub-clusters are formed which leads to efficient classification of records under privacy constraints thereby achieving less memory cost and increased precision and recall values.

CONFLICT OF INTEREST

None

ACKNOWLEDGEMENTS

None

FINANCIAL DISCLOSURE

None

REFERENCES

[1] Das K, Bhaduri K, Gupta H K. [2017] A local asynchronous distributed privacy preserving feature selection algorithm for large peer-to peer networks. Journal of Knowledge and Information Systems, 24(3): 341-367.

[2] Urmela S, Nandhini M. [2017] Approaches and Techniques of Distributed Data Mining. International Journal of Engineering and Technology (IJET), 9(1): 63-76.

[3] Alfredo Cuzzocrea. [2017] Models and algorithms for high-performance distributed data mining. Elsevier Journal of Parallel and Distributed computing, 73(93): 281-283.

[4] Fu Y. [2012] Distributed Data Mining: An Overview. In: Newsletter of the IEEE Technical Committee on Distributed Processing, 5-9.

[5] Breiman L. [1996] Pasting small votes for classification in large databases and on-line. Machine Learning, 36:85-103.

[6] Atisha Sachan. [2016] A Survey on Recommender Systems based on Collaborative Filtering Technique. International Journal of Innovations in Engineering and Technology (IJIET), 2 (2): 8-14.

[7] Ganga Devi SVS. [2014] A Survey on Distributed Data Mining and Its Trends. International Journal of Research in Engineering & Technology (IJRET), 107-120.

[8] Josenildo Costa da Silva, Matthias Klusch. [2006] Inferences in Distributed Data Mining. Engineering Applications of Artificial Intelligence, 19:363-369.

[9] Kargupta, Kamath Chan. [1999] Distributed and Parallel Data Mining: Emergence, Growth and Future Directions. Advances in Distributed Data Mining, (eds.). Hillol Kargupta and Philip Chan AAAI Press, 407-416.

[10] Kawuu W Lin, Sheng-Hao Chung. [2006] A fast and resource efficient mining algorithm for discovering Frequent patterns in distributed computing environments. Journal of Future Generation Computer Systems, 52:49-58.

[11] Koren Y. [2015] Tutorial on recent progress in collaborative filtering. In Proc. of the 2nd ACM Conference on Recommender Systems, 8-67.

[12] [dataset] Job Recruitment Dataset. https://github.com/datameet.

[13] Park BH, Kargupta H. [2002] Distributed Data Mining: Algorithms, Systems, and Applications. In. Data mining handbook.

[14] Nandhini M, Urmela S. [2016] Clustered Collaborative Filtering Approach for Distributed Data Mining on Electronic Health Records. International Journal of Control Theory and Applications (IJCTA), 9(3):81-91.

[15] Baik S, Bala J. [2004] A Decision Tree Algorithm for Distributed Data Mining: Towards Network Intrusion Detection. Computational Science and Its Applications – (ICCSA), 3046:206-212.

[16] Pandey TK, Panda N, Sahu PK. [2012] Improving performance of distributed data mining (DDM) with multi-agent system. International Journal of Computer Science Issues (IJCSI), 9(2):74-82.

[17] Tsoumakas G, Vlahavas I. [2008] Distributed Data Mining. Encyclopedia of Data Warehousing and Mining, 709-715.

[18] Vinaya Sawant, Ketan Shah. [2013] A review of Distributed Data Mining using agents. International Journal of Advanced Technology & Engineering Research (IJATER), 3(5):27-33.

[19] Xiaoyuan Su, Khoshgoftaar Taghi M [2009] A Survey of Collaborative Filtering Techniques. Advances in Artificial Intelligence.

[20] Yan Li, Changxin Bai, Chandan K Reddy. [2016] A distributed ensemble approach for mining health care data under privacy constraints. Journal of Information Sciences, 330: 245-259.

ARTICLE

APPLICABILITY OF DEEP LEARNING TECHNIQUES IN RECOMMENDER SYSTEMS

K.U. Kala*, M. Nandhini

Department of Computer Science, Pondicherry University, INDIA

ISSN 0976-3104

ABSTRACT

Recommender Systems (RecSys) have been used in various areas since the dawn of the Internet. State-of-the-art RecSys approaches rely on Machine Learning (ML) and Deep Learning (DL) in order to create more accurate and personalized recommendations for users. These DL techniques have been gaining the momentum due to its performance in high quality recommendations. Here we are reviewing DL based RecSys models. The focus is on the DL techniques such as Multilayer Perceptron, Auto encoder, Convolutional Neural Network, and Recurrent Neural Network and their effectiveness in the area of Recommender Systems. The selected 21 papers are categorized according to the DL techniques applied and extracted the details of recommender System type, applications domain, Data Set etc. This review helps the developers and researchers to get a comprehensive idea of the currently used DL techniques for various RecSys models, which will help them for finding most accurate DL technique for their RecSys and dataset.

KEY WORDS
Deep Learning, Recommender System Models, Collaborative Filtering, Content Based Filtering

Received: 30 Sept 2018
Accepted: 03 Dec 2018
Published: 8 Jan 2018

***Corresponding Author**
Email: kalaunni88@gmail.com
Tel.: +919656847815

INTRODUCTION

The explosive growth of information and their frequency is overwhelming in this information processing era. Information in the form of computer interpretable data is parsed and processed from one end point to another across a wide range of platforms and devices around the world. With the availability of huge amounts of data and content accessible to users, the exploration of the data becomes difficult due the number of choices at hand, which creates a problem for all parties involved. The content creators have a hard time to get their work to relevant users, the users have a hard time finding this content and the company providing the service where the content resides on are faced with the problem of providing the right content for the right users, and in many times, are forced to prioritize the most popular content for all users.

RecSys concern themselves act as the foundations of these challenges. In order to provide accurate recommendations for a given individual, the process at hand must be analyzed for personalized recommendations to prevail over blind recommendation that do not take any features regarding the user into account. Providing personalized and recommendations are a challenging task that many entities deal with and prioritize today. Companies want to better their services by providing personalized recommendations to their users for a multitude of reasons, such as the exploration of their data, prioritization or awareness. Classical approaches such as Collaborative Filtering (CF) and Matrix Factorization (MF) have previously prevailed in this area of interest and some systems depend on Ensemble Methods (EM) to create more accurate and personalized recommendations for their users [1, 2, 3, 4, 5].

Nowadays DL has become a popular approach in a wide range of areas such as image recognition, natural language processing, automatic speech recognition and biomedical informatics and seems to prevail in classification tasks. Therefore, it is of interest to see if different type of network architectures can be applied to the problem of recommendation in order to create personalized recommendations by using DL. It is of interest to see investigate if it is possible to represent the problem of recommendation as a multiclass classification problem, in order to analyze what kind of DL networks are applicable for creating multi-feature personalized recommendations. Some promising research area is emerging which gives motivation to use DL as a tool for creating recommendations. With this paper we aim to explore this new promising area of research by exploring the chances of DL in RecSys.

Rest of the paper is organized as follows, Section II contains brief introduction of the various Recommender Systems exists in the literature, Section III contain the description of related survey works in the field of deep learning based recommender systems, Section IV contain the description of selected 21 deep learning based RecSys models, classified in terms of the different DL techniques used, Section V tabulated the extracted data from the selected papers. Section VI concludes review work with future directions and Section VII mention the acknowledgement statement.

RECOMMENDER SYSTEMS

Recommender Systems are everywhere and we use them every day, directly or indirectly, in our digital interactions: when we buy that book that Amazon recommends us based on our previous history, when we listen to that playlists tailored to our taste in Spotify, or when we watch with the family that that movie recommended in Netflix, and discover new friend connections in Face book, or read that news articles we care about that Twitter offers, or when we apply to that ideal job hinted by LinkedIn. RecSys help us finding that valuable item among an ocean of choices. It helps us to deal with choice overload; it assists people for

IIOAB JOURNAL
ISSN: 0976-3104

facing the difficulties of decision making with a choice among many options by a cognitive process. RecSys is an active and fast growing field of research.

MATERIALS AND METHODS

RecSys collect and exploit numerous sorts of info concerning users, products, and interactions between users and products to come up with a customized list of things that matches user's current wants. Sohail et al [6] categorized 8 types of recommender systems (RS) as shown in [Table 1]. These categories broadly cover the techniques which have been used by the masses or the current generation researchers are frequently applying it.

Table 1: Recommenders system categories and techniques

Types of RecSys	Subcategory	Techniques
Collaborative Filtering (CF) based RS	Item based	Association rule mining between preferences of neighbor of users, Rating, Choice of individuals for varied items, Similarity in the preferences of different users for common items, Tagging
	User based	
	Model based	Bayesian networks, clustering, Machine learning, Graph modeling
Reclusive Methods (RM) based RS	Heuristic method	Rule induction, nearest neighborhood, Rocchio's algorithm, tagging, rating, etc.
	Model based techniques	Bayesian networks, clustering, Machine learning, Graph modeling
	Web mining	Opinion mining, web usage mining, etc
Hybrid recommender systems	CF dominated RM	Techniques of CF, RM applied with each other in different combinations
	RM dominated CF	
	CF and RM coalesced into one	
	Subsequent Integration of separately applied CF and RM	
	Integration of CF and RM with (KBS)	Techniques of CF and RM are applied with KBS, and other fuzzy, social network, etc
	Integration of CF with other than RM	
	Integration of RM with other than CF	
Demographic filtering based RS		Correlation, similarity measures, etc
Knowledge based Recommender System (KBS)	Constraint based	Machine learning, Bayesian network, AI, etc.
	Case based	
Context Aware Recommender System	Location aware, Temporal, Trust aware	User feedback, AI techniques, machine learning, etc.
Social network based RS	Foafing, trade relationship, etc.	Similarities measures, user profiling, etc.
Soft Computing techniques based RS	Fuzzy genetics, fuzzy linguistics,	OWA, ORWA, fuzzy model, etc.

RELATED REVIEWS

DL based RecSys is become widely popular from 2016. Now it becomes a promising research area. Many recent short reviews are available in the literature that deals with the state of the art deep RecSys. The number of publications is increasing day by day in the area of DL based RecSys. The leading international conference RecSys by ACM begins to conduct regular workshops and conferences from the year 2016.

There is a plenty of literature reviews exists in the area of traditional RecSys. Even though there is a huge scope for systematic literature reviews on Deep RecSys, it is not that much explored. The prominent and most systematic review on DL based RecSys is by Shuai Zhang et al [7]. This survey lays a foundation in this area that can highly dependable for the researchers who wish to enter into this area. They are proving a classification scheme of current works in a well defined manner, state of the art research area and discussing challenges and open issues deeply.

Another recent survey, by Ayush Singhal et al. [8], contains the summary of DL based collaborative systems and application domains. The other paper gives the narrow narration about the deep RecSys. In [9], Rim Fakhfakh et al. give major emphasis on the Challenges and issues in DL based RecSys The all existing reviews are not systematic they just tries to summarize the works in this area of research.

Mu et al [10] carried out a detailed survey recently on the various techniques and gives more research direction in the area. With this paper, we aim to help the researchers, students, and practitioners working in the field of RecSys by exploring the scope of DL Techniques in their field. Our aim is to help them by the following contributions.

IIOAB JOURNAL
ISSN: 0976-3104

- A brief overview of state of the art DL approaches used along with RecSys.
- An overview of various RecSys models along with applied DL techniques and datasets, from the literature.

Our aim is to provide a comprehensive review of recent researches happened in the field of DL based RecSys for making an improvement in classic RecSys.

DL BASED RECSYS MODELS

DL is a field of Machine Learning that allows computational models that are composed of multiple processing layers of representation and abstraction that help to make sense of data such as text, image, sound and video. DL technique is a hot and emerging area in both data mining and machine learning communities. These models can be trained by either supervised or unsupervised approaches. DL models are initially applied to the field of Language Processing, Computer Vision and Audio, and Speech. It outperformed many state-of-the-art models. Later deep models have shown their effectiveness for various NLP tasks. These tasks include semantic parsing, machine translation, sentence modeling and a variety of traditional NLP tasks. DL has recently been proposed for building RecSys for both collaborative and content based approaches. DL becomes a powerful tool to tackle RecSys tasks such as music, news, fashion articles, and mobile apps recommendation. This paper takes a glimpse of current research in this field, which aims to identify new opportunities for research and industrial applications, to enhance the recommender experience.

Multilayer Perceptron based RecSys model

MultiLayer Perceptron [MLP] is a feed forward neural network. Between input and output layer multiple hidden layers. It is an efficient gradient descent based nonlinear function approximators for error minimization in the approximation of a function. This tries to define a mapping from $y=f(x;\theta)$ and learns the value of the parameters θ that results in the best function approximation. There are mainly 4 recommendation models that utilize multilayer perceptrons [11-15]. The pictorial representations of these models have shown in [Fig. 1].

He et al. [11] developed a general framework using MLP to model the user-item interaction matrix by capturing the non linear relationship. NCF technique replaces the matrix factorization(MF) and utilized Negative sampling for data size reduction, which improves the learning efficiency. The proposed CF model is compared with existing MF approaches on Pinterest and MovieLens datasets and showed statistically significant improvements on both datasets. Neural Collaborative filtering model is depicted in [Fig. 1(a)].

CCCFNet[12] is an extension of NCF for cross domain applications. CCCFNet consists of two neural networks one for users and other for items. In this model user items interactions are represented as a dot product in the last layer. It is a multi-view cross domain recommendations that makes use of two components for embedding content information. One is collaborative filtering factor used for representing user and item latent factors. Other one is content information component that matches user's preferences on item features and item features. The architecture model is at [Fig. 1(b)].

Cheng et al.[13] proposed another model for both regression and classification problems. Here it is used in Google play for app recommendations. The model has two components: wide and deep. Wide component is a simple linear model such as single layer perceptrons where as deep component is a multilayer perceptron. Memorization and generalization is made possible by using those components. In this memorization is achieved by wide component and generalization is achieved by the deep component. Compared to NCF both accuracy and diversity is improving in this model. For optimization stochastic back propagation is utilized. According to the predicted score recommendation list is generating. [4] Extends wide and deep model by incorporating a locally connected network by replacing the DL component, which helps to decrease the running time. Wide & DL Model architecture is depicted in [Fig. 1(c)]. [14] introduces DeepFM model as shown in [Fig. 1(d)], for alleviating the feature engineering problems such as solving which feature is selected for memorizing and which feature is for memorizing in wide and DL models. That is depends only on DL and factorization machines. Here higher order feature interactions are implementing via DL (MLP) and low order interactions through factorization machine. The prediction score is calculated by

$$\hat{r}_{u,i} = \sigma\left(y_{FM}(x) + Y_{MLP}(x)\right)$$

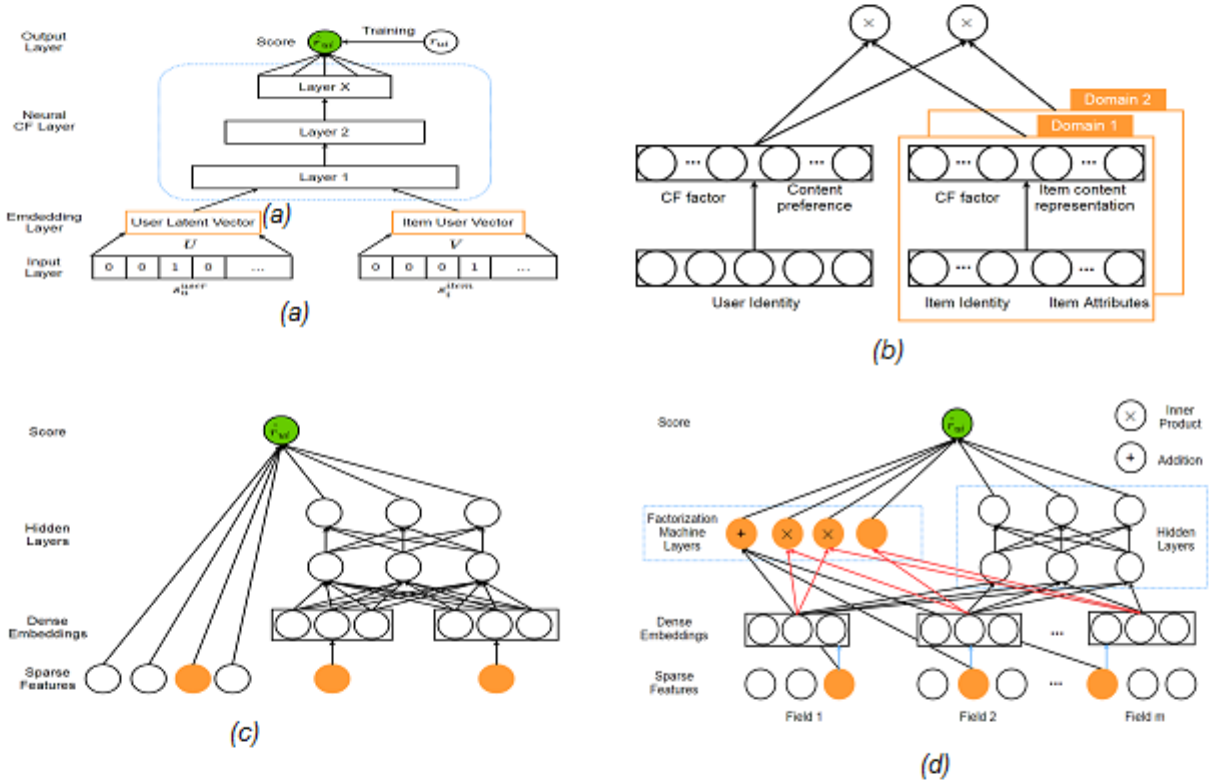


Fig. 1: MultiLayer Perceptron based RecSys Models (a. Neural Collaborative Filtering[11], b. CCCFNet[12], c. Wide & DL Model[13] d. DeepFM Model[14])

Zhang et al.[15] propose a hashing based DL framework called Discrete DL (DDL). It maps users and items to Hamming space. From that hamming space a user's preference for a particular item can be calculated efficiently by using hamming distance. Online recommendation efficiency is improved significantly by this computation scheme. Cold start problem and data scarcity problems are also alleviated by using discrete DL model by unifying item content information and user-item interaction. The extraction of effective item representation from the item content information is done by applying Deep Belief Network (DBN). DDL provides a good trade-off between recommendation efficiency and accuracy.

Auto Encoder based RecSys model

An auto encoder is a trained neural network that attempt to copy its input to its output. For describing the representation code of the input, it has a hidden layer h. The network consists of two parts: an encoder function h =f(x) and a decoder function r = g (h) that produces a reconstruction. Four auto encoder based RecSys are extracted from the literature [16-22] are shown in [Fig. 2.]

Sedhain et al. [16] proposed AutoRec, an auto encoder based RecSys. The aim of AutoRec is the reconstruction of inputs such as user partial vectors r^u or item partial vectors r^i in the output. Corresponding to both inputs two variations are there U-AutoRec (User based) and I-AutoRec (Item based). The reconstruction function for the input r^i in I-AutoRec is

$$h(r^i;\theta) = f(W.g(V.r^i + \mu) + b)$$

Where $f(.)$ and $g(.)$ are the activation functions, W,V,μ,b are parameters. While considering the performance I-AutoRec is better than u-AtoRec. Here activation function combinations, moderate increase in hidden unit size, adding more layers will increase the capacity and performance of AutoRec. I-AutoRec model is shown in the [Fig. 2(a)]. Strub et al. [17] extends the AutoRec to make it more robust by employing the de-noising techniques and including user side information such as item description and user profiles for mitigating the cold start problem. This model is known as Collaborative Filtering Neural Network [CFN], which also have two variants I-CFN and U-CFN taking r^i and u^i as input respectively. In this correption approaches such as salt and pepper noise, Gaussian noise and masking are utilized to deal with missing elements. In CFN Side information is integrated with every layer that will help to improve accuracy, training process speed and make the model to be more robust.

Auto encoder based collaborative filtering [ACF] proposed by Ouyang et al [18] is the first one in this type of RecSys. It deal with integer ratings (1-5), it divides the rating into five partial vectors. ACM predicts rating by summarizing each entry of the five vectors, and then scaled by the maximum rating 5. RBM is used t pre-train the parameters as well as to avoid local optimum. Short comings of this model are it can only deal with integer ratings and while decompose the rating vector that increase the sparse problem in input data and leads to inaccurate prediction. AutoRec, CFN and ACF are used for rating prediction whereas CDAE (Collaborative DE noising Auto-Encoder) proposed by Wo et al.[19] is used for ranking prediction.

IIOAB JOURNAL
ISSN: 0976-3104

User's feedback is the input to CDAE. The entry value is 1 whether the user likes the movie otherwise it is 0. Gaussian distribution is used for solving Gaussian noise problem. The reconstruction is defined as

$$h(\tilde{r}^{u}_{pref}) = f(W_2 \cdot g(W1 . \tilde{r}^{u}_{pref} + V_u + b_1) + b_2)$$

Where $V_u \in R^K$ denotes the weight matrix for user node. For each user this weight matrix is unique and it improves the performance too.

Wang et al [20, 21] proposes two Auto-Encoder integrated RecSys models: CDL (Collaborative DL) and CDR (Collaborative Deep Ranking) CDL for rating prediction where as CDR is for top n recommendations in a pair wise frame work. CDL uses Stacked De-noising Auto-Encoder [SDAE]. CDR outperforms CDL in their experiments. They are similar in structure and different in some iteration. Both make use of two tightly coupled components, one is a deep neural network used as a perception component and the other is a task specific component. A frame work is proposed by Li et al. [22] for unifying DL approaches with collaborative filtering model. It is called Deep Collaborative Filtering Framework. It is an easy and well defined frame work for incorporating DL techniques in collaborative filtering. The framework is formulated as follows

$$\arg\min_{U,V} l(R, U, V) + \beta(||U||_F^2 + ||V||_F^2) + \gamma L(X, U) + \delta L(Y, V)$$

Where β, γ, δ are trade off parameter, X, Y are side information l(.) is the lost and $\gamma L(X, U) + \delta L(Y, V)$ is the hinges for connecting deep and collaborative models.

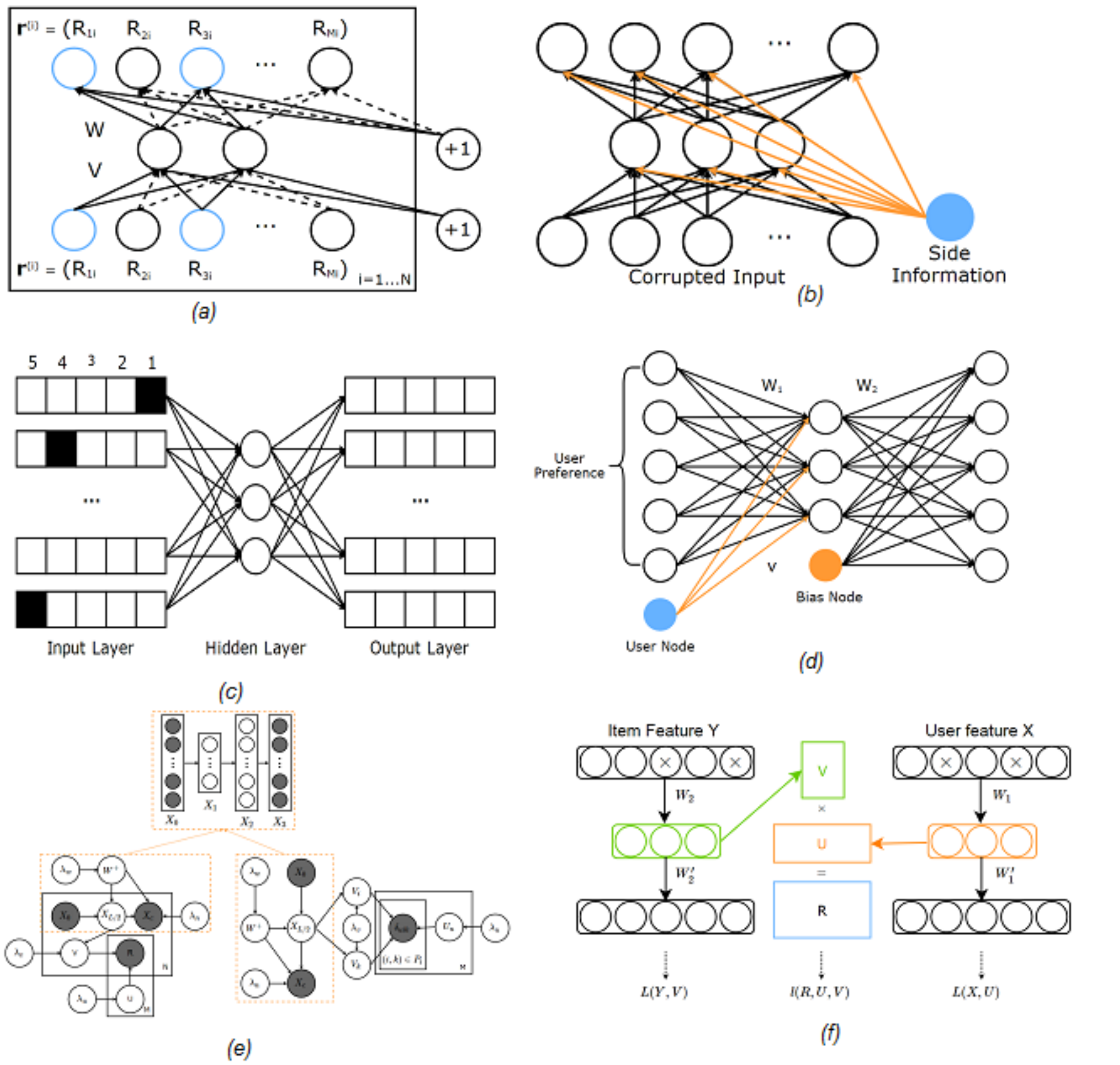


Fig.2: AutoEncoder based RecSys Models. (a). AutoRec Model[16], (b). CFN Model[17], (c). ACF Model[18], (d). CDAE Model[19], (e). Graphical Model of CDL(left) and CDR (Right)[20,21], (f). Deep Collaborative filtering Framework [22]

…………………………………………………………………………………………………..

THE IIOAB JOURNAL
COMPUTER SCIENCE

IIOAB JOURNAL ISSN: 0976-3104

Convolutional Neural Network based RecSys model

Convolutional Neural Networks[CNN] are a specialized kind of neural network for processing data that has a known grid-like topology such as time-series data [1-D grid], and image[2-D grid] of pixels. In CNN convolution is used in place of matrix multiplication in at least one of their layers otherwise it is a simple neural network [23-27]. The models are depicted in [Fig.3].

Gong et al. [23] solves hash tag RecSys as a multiclass classification problem. It is an attention based model. The part of the proposed model are global channel, which is made up of max pooling layers and convolutional filters, and local channel which is the attention layer for selecting trigger words for tagging. All words are imputed to the global channel where as local channel is used for selecting the trigger words. Nguyen et al. [24] proposed a personalized tag RecSys .in this paper they are extracting visual features from the images by using max pooling layer of CNN. For differentiating relevant and irrelevant tag according to a particular person , a Bayesian personalized Ranking algorithm is utilized. DeepCoNN(Deep Cooperative Neural Network) proposed by Zheing et al[25] incorporated two CNNs: one for user behaviors and another for item reviews. Factorization machines are used to find the interaction between two CNNs in the last layers for rating predictions. It combines the benefits of both CNN and Matrix factorization for solving scarcity problem by different layers as shown in the [Fig.3(c)].

ConvMF [26] is another model which utilizes probability matrix factorization along with CNN. Item representations are learned by using CNN and task specific recommendation are performed using PMF. The structure is similar to the CDL whereas instead of Auto-Encoder here CNN is used. Wen et al.[27] propose a dance background recommendation system that utilize CNN for image extraction. It focuses on dancers digital footprints images that they have browsed, liked, or used previously. To support the recommendation system, this work also proposes a Deep MF model based on PMF that effectively combines a content-based method and the conventional rating-based method. The content-based method uses the image's visual content to do the recommendation, and the visual content of a dance image is represented by both an object feature and a style feature. The detailed architecture is shown in Fig. 3(e)].

Recurrent Neural Network based RecSys model

Recurrent neural networks are a family of neural networks for processing sequential data x1, x2,...., xn. When feed forward neural networks are extended to include feedback connections, they are called recurrent neural networks. LSTM and GRU are two different variations of RNN. RNN viewed the user interest as a sequence prediction technique. Similar sequence are identified and recommended. The concepts used in RNN for RecSys is extracted [28-32] and depicted in [Fig. 4].

Hidasi et al. [28] proposed a RecSys model for session based recommendation based on Recurrent Neural Networks (RNN). Session based RecSys considers users current login interests only for recommendations. It may lead to scarcity of training data. Here the proposed model efficiently implemented session based RecSys by using GRU. If there is N number of items the state of the item is represented as 1-N encodings. And tries to assign the session value for each item as 1 if it is active in that session otherwise it is 0. Likelihood and session based parallel mini batches algorithm is used for further processing of the output. Tan et al. [29] modified the model [28] by changing the input from 1-N encodings to click sequences and they add necessary preprocessing and dropout procedures for handling those inputs. They train the model first by complete input and then tune it with most recent inputs. For decreasing the number of parameters they use item embedding techniques, this leads to faster computation. Recurrent Recommender Network (RRN) [30] is a non parametric model for recommendation built on Recurrent Neural Networks. Here two LSTMs are used for modeling seasonal evolution of items and user preferences over time. One LSTM is for user state $\mathbf{u}_{u,t}$ and the other for item state $\mathbf{v}_{i,t}$. This model considered user stable long term interests as well as dynamic short term interests also. The predicted rating of j given by user i at time t is represented as

$$\hat{\mathbf{r}}_{ui|t} = \mathbf{f}(\mathbf{u}_{ut}, \mathbf{v}_{it}, \mathbf{u}_u, \mathbf{v}_i)$$

Where $\mathbf{u}_u, \mathbf{v}_i$ are learned from matrix factorization and the others are from LSTM.

Like attention based MLP and CNN, attention mechanism can also incorporated with RNN [31]. It helps to learn the sequential property and for recognizing informative words from micro blogs for hash tag recommendation. Here LSTM is utilized for learning hidden states and also attention based is based on LDA distribution after the nonlinear transformation and softmax normalization. Cross entropy minimization is used for training this model. Beutel et al. [32] created a deep context aware RecSys using Latent Cross to include contextual features more expressively. Latent cross is utilized to get the element wise product of the neural network hidden states and the context embedding. It uses different contexts along with ratings for video recommendation based on Recurrent Neural Network. The deep RNN architecture is shown in the [Fig. 4(e)].

ISSN: 0976-3104

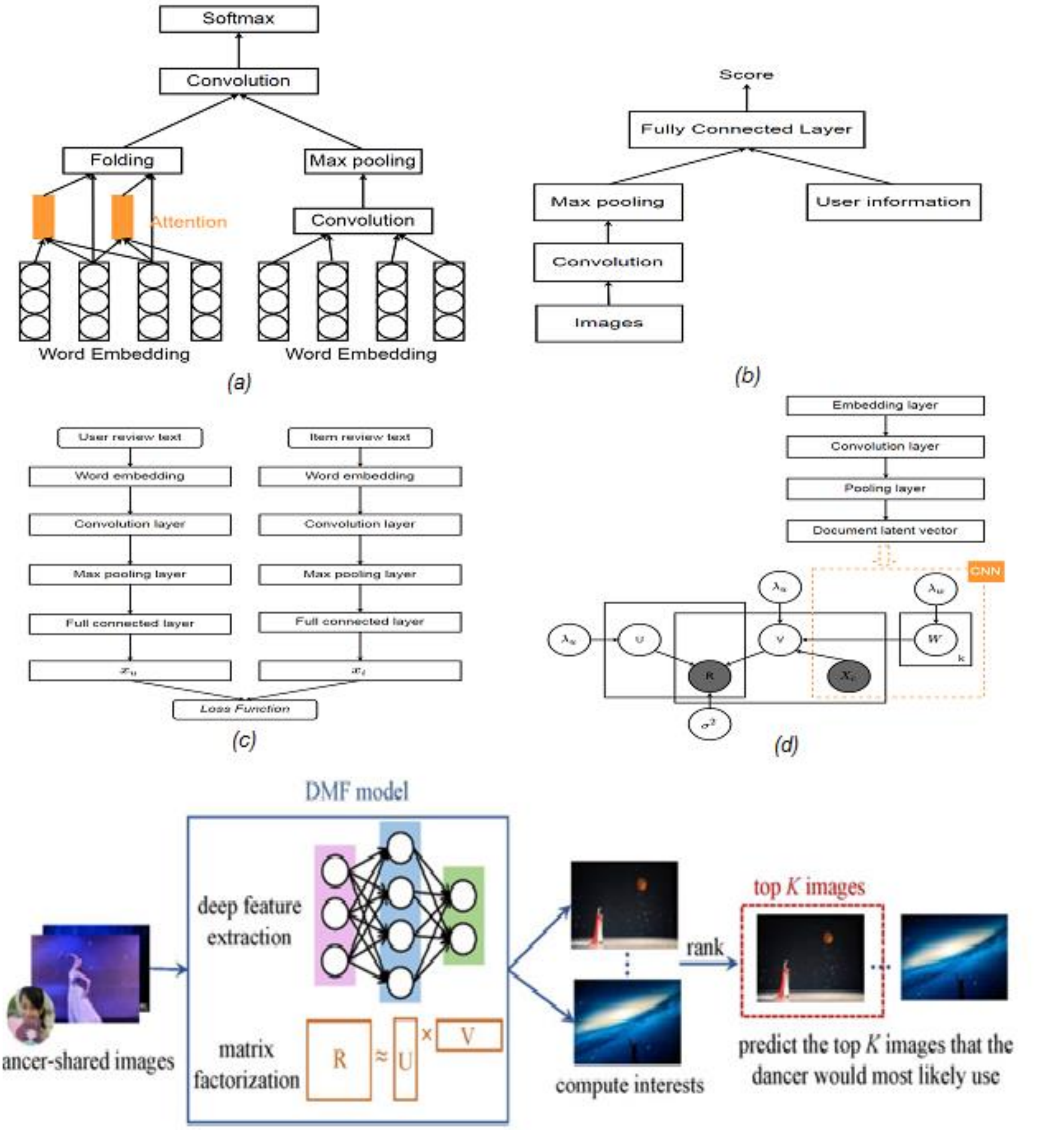


Fig. 3: CNN based RecSys Models. (a). Attention Based CNN model[23], (b). Personalised CNN Tag Recommendation Model[24], (c). DeepCoNN Model[25] (d). ConvMF Model[26], (e). Dance background image recommendation system.[27]

....

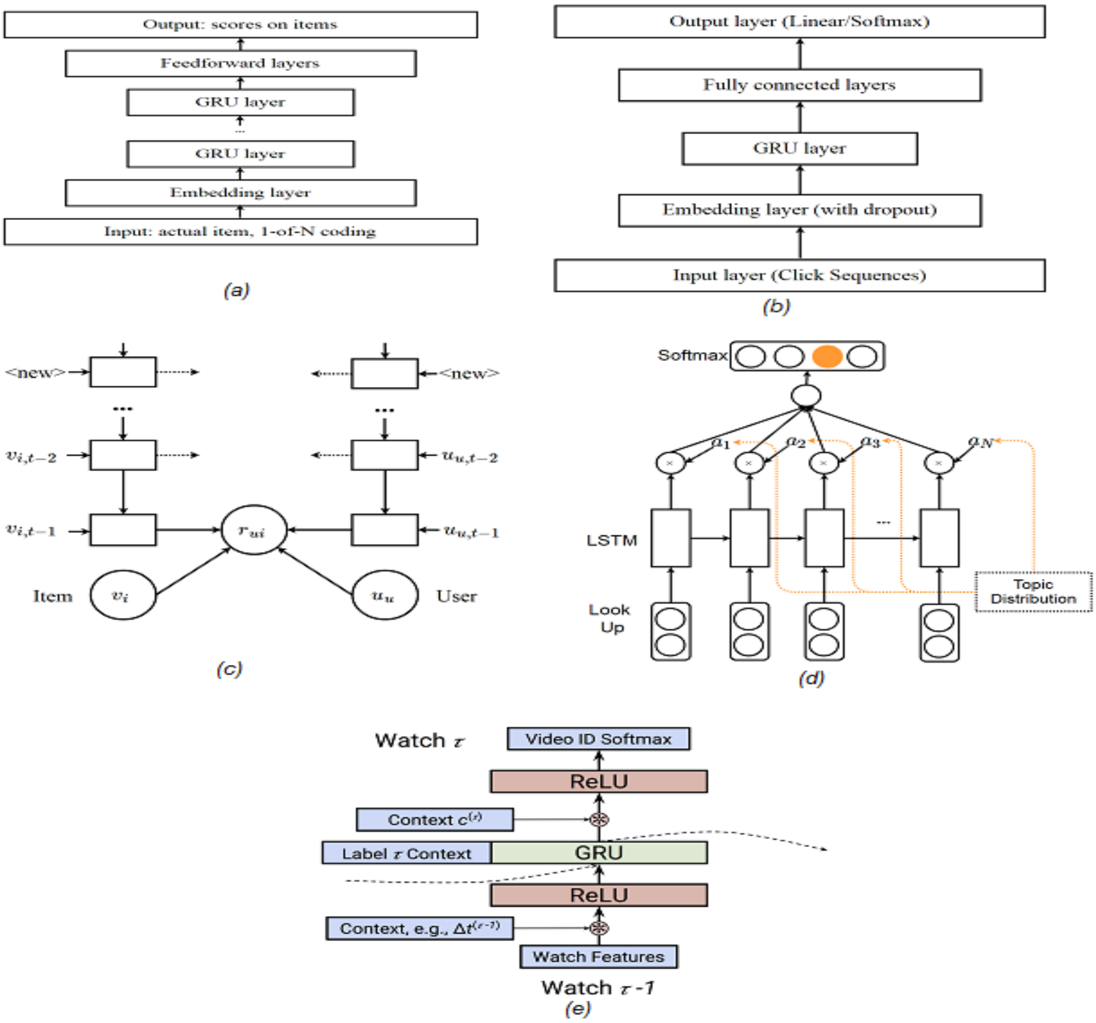


Fig. 4: RNN Based RecSys Models. (a). Session-based recommendation With RNN[28], (b). Improved Session-based recommendation With RNN[29], (c). Recurrent Recommender Network (RRN) Model [30], (d). Attention based RNN Model for Tag Recommendation.[31], (e). Latent cross based RecSys architecture.[32]

DATA EXTRACTION

The data extracted from the selected papers which utilized the concept of DL for RecSys Models are tabulated as in [Table 3]. This review is focused on the 4 DL techniques such as Multilayer perceptrons, Autoencoder, Convolutional Neural Networks and Recurrent Neural Networks.

Table 2: Deep learning techniques, corresponding RecSys Models and used application domains

DL Techniques	RecSys Model	RecSys Type	Concepts used	Application Domain
Multilayer Perceptions	Neural Collaborative Filtering[11] Model	Collaborative Filtering	MLP is used for user-item interactions and nonlinearities. Negative Sampling	Movie Recommendation
	CCCFNet[12]	Content and Collaborative Filtering	Cross Domain Recommendation Multi- view modeling	Movie and Music cross domain
	Wide and Deep Learning Model[13]	Collaborative Filtering	Single layer Perceptron Multi-layer Perceptron	Google App domain
	DeepFM Model[14]	Collaborative Filtering	Factorization Machine Multilayer perceptron	CTR Prediction
	Discrete DL[15]	Content based RecSys	Hashing Deep belief network	E-Commerce
Auto Encoder	AutoRec[16]	Collaborative Filtering	User based representation Item based representation	Movie Recommentation
	CFN[17]	Collaborative Filtering	Denoising	Movie Recommendation Jock Recommendation
	ACF[18]	Collaborative Filtering	Integer rating RBM	Movie Recommendation

	CDAE[19]	Collaborative Filtering	Ranking prediction Gaussian distribution	Movie Recommendation
	CDL[20]	Collaborative Filtering	Rating prediction SDAE	Article Recommendation
	CDR[21]	Collaborative Filtering	Ranking prediction Implicit feedback	Article recommendation
	DCIF[22]	Collaborative Filtering	Stacked DE noising	Article Recommendation Movie Recommendation
Convolutional Neural Network	Attention based CNN Model[23]	Collaborative filtering	Multi class classification Attention learning	Hash tag Recommendation
	Personalised CNN Model[24]	Collaborative filtering	Image feature extraction	Hash tag Recommendation
	DeepCoNN[25]	Content based filtering	Combines CNN and MF	Product Recommendation
	ConMF Model[26]	Context aware Recommendation	Probability Matrix Factorization	Document recommendation
	Dance background image recommendation model[27]	Content based Recommendation	Probability Matrix Factorization Deep feature extraction	Image recommendation
Recurrent Neural Network	Session based recommendation based on RNN[28]	Content based filtering	GRU Parallel mini batch algorithm	You tube video recommendation
	Improved Session based recommendation with RNN[29]	Content based filtering	Embedding techniques	You tube video recommendation
	RRN[30]	Collaborative filtering	Non parametric model	Video Recommendation
	Attention based RNN Model[31]	Collaborative filtering	Attention mechanism Non linear transformation	Hash tag recommendation
	Latent cross based context aware recommendation Model[32]	Context Aware Recommendation	Latent cross technique	Youtube video recommendation

CONCLUSION AND FUTURE WORK

This paper describes the literature review of the various DL techniques used in the field of RecSys. The major emphasis is on the DL architectures and their working on each paper on study. Compared to Data Mining techniques, DL techniques are more effective for RecSys because nowadays RecSys are dealing with big data, especially the volume of dataset is huge. Even though there are large opportunities for DL based RecSys, they are not explored yet. This paper can be a base for the researchers to start their research in this filed.

The conventional readily available datasets are only used for experimentation in the RecSys. Recommendation systems are still based on the conventional applications such as ecommerce site, movie, music, etc., with the help of DL, the scope of RecSys can spread to the new, complicated and unexplored fields by utilizing the real time datasets. The current research literature has focused on the collaborative and content based RecSys. In future deep RecSys have great opportunities in research , they include: for the better understanding of the users and items, for multitask learning, multi view RecSys for improving scalability, for session based RecSys, cross domain recommendations, context aware recommendations, etc.. The DL seems to be a powerful solution to overcome the limitations in this field and enhance the recommendation systems experience.

CONFLICT OF INTEREST
None

ACKNOWLEDGEMENTS
This Survey is performed as an initiation to the Ph.D work on the topic Deep Learning based Recommender Systems. There is no funding source(s) involved in this research.

FINANCIAL DISCLOSURE
None

REFERENCES

[1] Aggarwal CC. [2016] Recommender Systems, Springer, USA, ISBN: 9783319296593
[2] Su X, Khoshgoftaar TM. [2009] A Survey of Collaborative Filtering Techniques, Advances in Artificial Intelligence, 9: Article ID 421425, pp19, DOI:10.1155/2009/421425
[3] Isinkaye FO, Folajimi YO , Ojokoh BA. [2015] Recommendation systems: Principles, methods and evaluation, Egyptian Informatics Journal, 16(3): 261-273.
[4] Felfering A, Russ C, Isak K. [2006] Knowledge-Based Recommendation: Technologies and Experiences from Projects, Proceedings of the 2006 conference on ECAI

2006: 17th European Conference on Artificial Intelligence August 29 -- September 1, 2006, Riva del Garda, Italy, pp 632-636.
[5] Adomavicius G, Tuzhilin A. [2005] Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions, IEEE Transactions on Knowledge and Data Engineering, 17(6): 734-749.
[6] Shail SS, Siddiqui J, Ali R. [2017] Classification of Recommender System: A Review, JESTR, 10(4):132-153.
[7] Shuai Z, Yao L, Sun A. [2017] Deep Learning based Recommender System: A Survey and New Perspectives. CoRR abs/1707.07435 (2017).
[8] Singhal A, Sinha P, Pant R. [2017] Use of Deep Learning in Modern Recommender System: A Summary of Recent Works, International Journal of Computer Applications 180(7):17-22.
[9] Fakhfakh R, Ammar AB, Amar CB. [2017] Deep Learning-based Recommendation: Current Issues and Challenges, IJACSA, 8 (12): 59-68.
[10] Mu R. [2018] A survey of Recommender Systems Based on Deep Learning, IEEE Access, 6:69009-69022.
[11] He X, Liao L, Zhang H, et al. [2017] Neural collaborative Filtering. In Proceedings of the 26th International Conference on World Wide Web. International World Wide Web Conferences Steering Committee, 173-182.
[12] Lian J, Zhang F, Xie X, Sun G. [2017] CCCFNet: A Content-Boosted Collaborative Filtering Neural Network for Cross Domain Recommender Systems. In Proceedings of the 26th International Conference on World Wide Web Companion. International World Wide Web Conferences Steering Commi.ee, 817-818.
[13] Cheng H, Levent KOC, Harmsen J, et al. [2016] Wide & deep learning for recommender systems. In Proceedings of the 1st Workshop on Deep Learning for Recommender Systems. ACM, 7-10.
[14] Guo H, Tang R, Ye Y, Li Z, et al, 2017. DeepFM: A Factorization-Machine based Neural Network for CTR Prediction. IJCAI. 2782-2788.
[15] Zhang Y, Yin H, Huang Z et al. [2018] Discrete Deep Learning for Fast Content-Aware Recommendation. In WSDM 2018: 11th ACM International Conference on Web Search and Data Mining, February 5–9, 2018, Marina Del Rey, CA, USA. ACM, New York, NY, USA, 9 pages. DOI:10.1145/3159652.3159688
[16] Sedhain S, Menon AK, Xie SL. [2015] Autorec: Autoencoders meet collaborative €ltering. In Proceedings of the 24th International Conference on World Wide Web. ACM, 111–112.
[17] Strub F, Mary J. [2015] Collaborative Filtering with Stacked Denoising AutoEncoders and Sparse Inputs. In IPS Workshop on Machine Learning for eCommerce, https://hal.inria.fr/hal-01256422v1, accessed on 30 Aug 2018.
[18] Ouyang Y, Liu W, Rong W, et al,. [2014] Autoencoder-based collaborative Filtering. In International Conference on Neural Information Processing. In: Loo CK, et al., (eds) Neural Information Processing. ICONIP 2014. Lecture Notes in Computer Science, vol 8836, pp 284-291. Springer, Cham.
[19] Wu Y, DuBois C, Zheng AX, Ester M. [2016] Collaborative denoising auto-encoders for top-n recommender systems. In Proceedings of the Ninth ACM International Conference on Web Search and Data Mining. ACM, 153-162.
[20] Wang H, Wang N, Yeung D. [2015] Collaborative deep learning for recommender systems. In Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, 1235-1244.
[21] Ying H, Chen L, Xiong Y, Wu J. [2016] Collaborative deep ranking: a hybrid pair-wise recommendation algorithm with implicit feedback. In Paci€c-Asia Conference on Knowledge Discovery and Data Mining. Springer, 555–567, DOI:10.1007/978-3-319-31750-2_44
[22] Li S, Kawale J, Fu Y. [2015] Deep collaborative Filtering via marginalized denoising auto-encoder. In Proceedings of the 24th ACM International on Conference on Information and Knowledge Management. ACM, 811-820.
[23] Gong Y, Zhang Q. [2016] Hashtag Recommendation Using Attention-Based Convolutional Neural Network.. In IJCAI. 2782–2788
[24] Hanh TH Nguyen, Martin Wistuba, Josif Grabocka, Lucas Rego Drumond, Lars Schmidt-.ieme. [2017] Personalized Deep Learning for Tag Recommendation. Springer International Publishing, Cham, 186–197, DOI:10.1007/978-3-319-57454-7
[25] Zheng L, Noroozi V, Yu PS. [2017] Joint Deep Modeling of Users and Items Using Reviews for Recommendation. In Proceedings of the Tenth ACM International Conference on Web Search and Data Mining (WSDM '17). ACM, New York, NY, USA, 425–434. DOI:10.1145/3018661.3018665
[26] Kim D, Park C, Oh J, et al., [2016] Convolutional matrix factorization for document context-aware recommendation. In Proceedings of the 10th ACM Conference on Recommender Systems. ACM, 233-240.
[27] Jiqing W, She J, Li J, Mao H. [2018] Visual Background Recommendation for Dance Performances Using Deep Matrix Factorization. ACM Transactions on Multimedia Computing, Communications, and Applications. 14:1-19. DOI:10.1145/3152463
[28] Hidasi B, Karatzoglou A, Baltrunas L, Tikk D. [2015] Session-based recommendations with recurrent neural networks. International Conference on Learning Representations. Proceedings of the 10th ACM Conference on Recommender Systems, September 15-19, 2016, Boston, Massachusetts, USA, DOI:10.1145/2959100.2959167]
[29] Tan YK, Xu X, Liu Y. [2016] Improved recurrent neural networks for session-based recommendations. In Proceedings of the 1st Workshop on Deep Learning for Recommender Systems. ACM, 17-22.
[30] Wu C, Ahmed A, Beutel A, et al., [2017] Recurrent recommender networks. In Proceedings of the Tenth ACM International Conference on Web Search and Data Mining. ACM, 495-503.
[31] Li Y, Liu T, Jiang J. et al. [2016] Hashtag recommendation with topical attention-based LSTM. In Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics, 943-952.
[32] Beutel A, Covington P, Jain S, et al. [2018] Latent Cross: Making Use of Context in Recurrent Recommender Systems. In WSDM 2018: The Eleventh ACM International Conference on Web Search and Data Mining, February 5–9, 2018, Marina Del Rey, CA, USA. ACM, New York, NY, USA, DOI:10.1145/3159652.3159727

ARTICLE

ANALYSIS OF SURFACE-BASED MORPHOMETRIC OF HIPPOCAMPAL SUBFIELD VOLUMETRY IN ALZHEIMER'S DISEASE AND MCI

S.Sambath Kumar*, M. Nandhini

Department of Computer Science, Pondicherry University, INDIA

ABSTRACT

Background: *Changes in Hippocampal subfield volumeof patients with Alzheimer's Disease and Mild Cognitive Impairment from structural Magnetic Resonance Imaging using the techniques like free surfer and FIRST. The Hippocampus is one of the main areas used in neuroimaging studies. Hippocampus is responsible for memory and learning because of which it can be considered as one among the important biomarker for the neuro diseases. Hippocampal subfield even though being an important region for diagnosis of the AD diseases, is not being used in most of the study because of the complexities such as semi-automated segmentation and manual segmentation.* ***Methods:*** *To overcome existing problems we have modeled a novel subfield segmentation pipeline which consists of three stages. Those are Subfield information extraction, hippocampal segmentation and atlas mean surface calculation.* ***Results:*** *Experimental implementation on ADNI dataset it is proved that our model provides high accuracy than the other models comparatively for diagnosing the disease.* ***Conclusions:*** *Our proposed approach successfully analyzed the hippocampus subfield volume from MRI scan for AD and MCI disease.*

INTRODUCTION

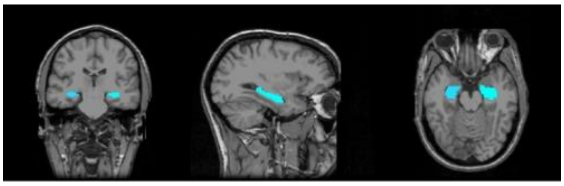
KEY WORDS
Hippocampus, subiculum, presubiculum, Magnetic Resonance Imaging (MRI), Alzheimer's disease, pre-processing.

Alzheimer Disease is one among the dreadful disease with has caused 700000 death in the year 2017 and It's estimated that the percentage may increase in the future.This disease effects the elders who are is aged more than 65 years. This disease is not been diagnosed properly it may also be fatal. Huge populations of about 40 million people are being after by this disease. It is also estimated that the growth maybe alarming such that in 2030, the affected populous maybe 76 million and in 2050 it may even nearly double to be 135 million. If this ratio continues nearly 30% of the world's population will be affected by this disease within the year 2080 [1,2].

The study of the hippocampus plays a vital role in the diagnosis of brain-related disorders such as Alzheimer's disease. Hippocampus is the area which summaries the long-term to short-term memory it is also one among the main part which gets affected by the Alzheimer's disease. Hippocampus is mainly used for learning and memory and it can be widely studied using neuroimaging Technologies [3]. Subfield volume grey matter surface deformation and total volume are the measures which are considered for the hippocampus [4].

Received: 11 Oct 2018
Accepted: 18 Dec 2018
Published: 10 Jan 2019

The subfield hippocampus information is mostly ignored as it is mostly related to the long-term study which is mostly done using semi or manual segmentation [5][6].Itis mostly not suitable for large-scale studies. The subfield scans is still challenging for 1.5T and 3T scans of MRI. The regional volume segmentation and cortical thickness is derived using the freesurfer tool. On using the volume, boundary error exists which makes it hard to analyze the image safe. FIRST is another software which gives good results for the hippocampus segmentation than the freesurfer tool [7][8]. Surface Atlas is constructed using both the freesurfer and the first which identify the hippocampus structural changes and different conditions.



(a) (b) (c)

Fig.1: The Hippocampal area for some relevant blue slice on the (a) coronal view (b) sagittal view (c) axial view for AD subject from MRI scan

....

The organization of this paper is as follows. Section II focuses on the background of the related works. It presents the technique of subfield volume changes, surface modeling using SPHARM and building a surface atlas in section III. Section IV discusses experimental and results of AD/MCI. Section V concludes the paper.

RELATED WORKS

***Corresponding Author**
Email: sambathkumars06@gmail.com
Tel.: 91-9445664612

The ADNI dataset is a 3D sMR image which comprises of the complete brain's structure. In the surface based morphometric analysis features the complete surface brain is considered for feature extraction. Various analyzing techniques and machine learning algorithms have been used along with these features for diagnosing the AD.Many clinical data is reorderedonly for few diseases such as Alzheimer's disease (AD), mild cognitive impairment (MCI),

IIOAB JOURNAL
ISSN: 0976-3104

depression, schizophrenia and many other neurological disorders based on hippocampal subfield can be analyzed. By combining hippocampal subfield with clinical data high accuracy could be achieved. Many weighted MRI scans are used to identifying the AD and MCI such as T1,T2, 1.5T, 3T, 4T and 7T. Hippocampal subfield analysis is done based on age, gender, subfield volume, education, cognitive functions, cortical sub regions and diseases. In this work, ADNI dataset has been used for classification of AD and MCI. This work has been compared with the existing work that uses cortical features and has achieved good accuracy. There are many classifier approaches for the AD and MCI patients using various hippocampal subfield volumes exists for different subjects(aMCI, HC, AD, MCI and LMCI) using different metrics (1.5, 3T and 7T) and different weighted MR images(T1, T2)[9-16,3]

Table -1: Classifier approach of the AD and MCI patients using different subfield volume

Author & year	Subfield Volume	Datasets	Metrics	Results
Dong woo kang et al.2018[9]	Education, Cognitive functions	77 subjects(aMCI-38,HC -39)	3T scan	Education years (hc&aMCI) Std.β=0.74,p-value<0.001,aMCI=Std.β=0.3,aMCI=0 .041
Fabian Bartel et al.2016[10]	Regional volume & Outline Reproducibility, cube algorithm	ADNI 80 subjects:HC-20,MCI-40, AD-20	T1 weighted MRI scans	Region Method (Manual: anterior-0.794, Middle-0.828, Posterior-0.756) FSL-FIRST: anterior-0.829, Middle-0.855, Posterior-0.798, Freesurfer: anterior -0.756, Middle-0.784, Posterior-0.721.
Paul .A.Yushkevich et al. 2015[11]	Cortical subregions& hippocampal subfields.	83 aMCI subjects.	T2 weighted MRI scans	Corrective learning from left part Mean-0.780, SD-0.027, Min-0.701, Max-0.853 and right part Mean- 0.777, SD-0.034, Min-0.689, Max-0.847
Stine K. Krogsrud et al.2014[12]	Hippocampal subfield regions age from 4 to 22 years	244 healthy subjects.	1.5T MRI scans. Validation(1.5 T & 3T MRI scans	-
Renaud la joie et al.2013[13]	Subfield volume(Complementary analyses, operating characteristic analyses and Non-parametric group comparisons)	ADNI 75 subjects:HC-40,aMCI-17, AD-18	-	ROC curve = 0.88 and 0.76,p=0.05
Laura E.M. et al.2013[14]	Linear regression and continuous independent variable	ADNI 54 patients with HC-29,aMCI-16, AD-9	7T MRI scan(ultra high speed0 .7mm^3)	Linear regression: ERC(CI=-0.07,B=-0.04) SUB(CI=-0.16,B=-0.04)
John Pulta, P. Yushkevich et al.2012 [15]	Template-based approach	Subjects 45: 28 Normal control,17 a MCI,	T2 weighted images	Hippocampal volume CA1 left p=0.001 right p=0.038,CA4/DG left p=0.002 right p=0.043. Reduced volume CA4/DG left p=0.029 right p=0.221.
Li shen et al. 2010[16]	Intraclass and Pearson correlations calculated and statistical analysis.	125 adult subjects with HC-38, aMCI =37, AD=11.	T1 weighted MRI scans	Freesurfer(p=0.004) manual method(p=0.428)range from 0.76-0.90. ICC range from 0.75-0.89.
SG Muller et al. 2011[3]	Stepwise regression analysis Pearson correlations.	50 elder subjects 25 NC, 25 AD.	4T MRI scans	ERC=IFRD-0.17, SFRD-0.29, DRD-0.20, Sub= IFRD-0.26, SFRD-0.31, DRD-0.22, CA1= IFRD-0.31, SFRD-0.41, DRD-0.41,CA1-2= IFRD-0.12, SFRD-0.16, DRD-0.15, CA3&DG= IFRD-0.35, SFRD-0.38, DRD-0.35.

IIOAB JOURNAL
ISSN: 0976-3104

From the above survey, we could infer that various surface-based analysis techniques are used for hippocampal analysis and hippocampal subfield volume segmentation. Most of the researchers use high dimensional scanned features which have increased the cost of memory and data redundancy. It's noted that subfield volume is high. But Segmentation of hippocampal subfield volume is analyzed and surface atlas of hippocampal subfield is built to reduce the data, high accuracy and memory usage to a far extent. Thus surface atlas is deployed along with the freesurfer and FIRST and their respective accuracies are being analyzed.

SUBJECTS AND METHODS

We have used a three-stage pipeline model. (a) From MRI scan Subfield information is extracted using freesurfer, (b)hippocampus segmentation is done using the FIRST, and (c) spherical harmonic basis functions is used for hippocampus surface modeling and calculating the mean surface [17]. Using the above three methods the surface Atlas is created for the hippocampal subfield using normal control people from the ADNI dataset.

Adni Neuroimaging Data

MRI image data set is downloaded from theAlzheimer's disease [18] Neuroimaging Initiative database (ADNI) (http://adni.loni.usc.edu/). ADNI website which also comprises the Magnetic resonance imaging,PET image datasets, SPECT, CSF, blood biomarkers combined with clinical assessment to improve the ad process. Adni database has images of three different stages in the Alzheimers disease [19]. From this database, the data can be downloaded where this database also monitors the regular research works done. Consist of totally 800 subjects which have been divided into subjects with early AD early or late MCI and normal control based on the age which must be within the range55 to 90. The primary goal of the adni is to improve the ad progress using these biomarkers[18]. The proposed work we use the MRI images. The MRI image is primarily classified into a fMRI and a sMRI where we utilize the sMRI images.

Analysis datasets

The baseline MR images downloaded from the ADNI (adni.loni.usc.edu) site using 1.5T and 3T scanners with the help of DICOM. This downloaded MR images incorporate with Mini-Mental State Examination (*MMSE*) score and Clinical Dementia Rating Scale(*CDR*) (or *CDR* = 0) for each and every subjects. The given subjects are primarily classified into three categories such as HC, MCI and AD based on the age which must be within the range55 to 90. We organize the dataset consisting of 687 subjects as follows.

1. 172 HC subjects: 93 male and 79 female; age SD=75.3±7.4 years, range = 55 -90; Mini-Mental State Examination(MMSE)=29.±1.2; the range= 25 -30.
2. 407 MCI subjects: early MCI 267 patients not converted into AD with 18 months(EMCI) and late MCI 140 (LMCI) patients who changed over to AD ; 212 male and 195 female; age ± SD=75.3±7 years, range 58-88 years; Mini-Mental State Examination (MMSE)=27.1±1.7; the range from = 24 - 30
3. 108 AD subjects: 65 male and 43 female; age SD=75.3±7.4 years, range = 55 -90; Mini-Mental State Examination(MMSE)=23.8±2; the range = 18 – 27.

Structural MRI analysis

Surface-BasedAnalysis is a method where the Cortical surface's geometrical model is used to derive the morpho metric measures. Among the numerous implementation of SBA we primary use free surfer brain visa and brain voyager. Taking the input as T1 weighted MRI image the SBA extracts cortical surface. Coronal surface displays two surfaces which are the Yellow line and the red line. Yellow line depicted as the inner boundary of the cortex which can also be called as a white surface. The Yellow line which acts as a surface boundary lies in between of the cortical grey matter and white matter. Whereas the Red Line boundary lies in between grey matter and CSF which can also be termed as pial surface[20]. Cortex is the composition of highly dense Triangles each of which are known as a face is being interconnected as a mesh which is being modeled as a surface model. The junction of each face is called a vertex. The three-dimensional coordinates X,Y and Z which are the parameters are being deducted from the extraction process of MRI. The surface can be subjected to many manipulations among which one is inflating it. All the area or being exposed during the inflation which is equivalent to unfolding the surface. Combining the area of the Triangles we get the cortex's surface area. Cortical thickness is the distance between the white and pial surfaces.

Segmentation of the subfield volume

On doing Hippocampus Subfield segmentation using the free surfer will we concentrate 8 volumes. The 8 volume represented as a probability maps each of which are a subfield all of them are listed below. The subfield volumes are CA1, CA2-3, CA 4-DG, Fimbria, Hippocampal -fissure Parasubiculum, Subiculum and others.

Using the first software hippocampus is split into two parts which are the left and right. Over this processing, the topology fix is then which verifies the spherical property and object connectivity of the hippocampus. All the probability maps are being masked. After the masking area outside the mask is assigned to be zero and there must be no zero values inside the mask for converting the zero values to non-zero values which are present inside the mask the Gaussian kernel is used. The size of the Gaussian kernel is [5 5 5] in our work. Updated values are assigned to the voxel in the hole. Thus we can obtain the updated probability map which is from P1 to P8. These are the next step of input data.

IIOAB JOURNAL
ISSN: 0976-3104

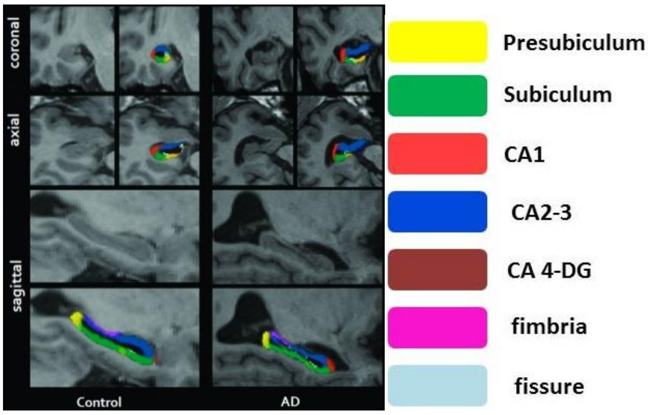


Fig. 2: Hippocampal subfield segmentation from freesurfer: Coronal view, axial view and sagittal view. The left images are healthy control and right images are ad subjects. The abbreviations are CA- Cornu'sammonia;DG-dentate gyrus.

Surface modeling using SPHARM

The binary object can be compared for the diagnosis directly. So we apply the spharm basic function to model the surfaces. This spharm method was developed by La Joie et al [13] to shape the 3D objects. Thus we use the three processing methods are spherical parameterization, expansion and registration. We should perform the bijective mapping between spherical coordinates and surface. The coordinates represented as ø and θ and surface point represented as V.

$V(\theta,ø)=(x(\theta,ø), y(\theta,ø), z(\theta,ø))^T$TheFourier transform is this used the preprocessing to define the three-dimensional surface from the three spherical functions[21]. Three spherical functions are transferred to three sets of Fourier coefficients. The hippocampal surface is expanded and registered.

Building surface atlas of hippocampal subfield mapping

Using the freesurfer we segmented 8 subfield volumes: The subfield volumes are CA1, CA2-3, CA 4-DG, Fimbria, Hippocampal -fissure Parasubiculum, Subiculum and others. This subfield segmentation on the basis of the Bayesian approach.Each 8 volume represented as a probability maps. Then we employ the spharm basic function to model the surfaces.

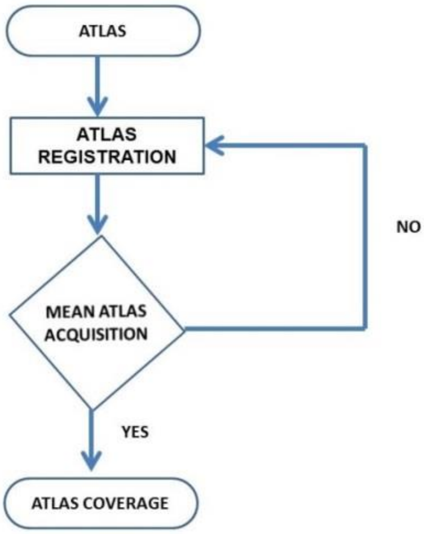


Fig.3: The flowchart for creating a surface atlas of the subfield.

Our example is as follows: atlases is the starting point of the surface, then register the atlas for aligning, then mean atlas acquisition for all the data. Then repeat atlas registration until the stopping point of the coverage of the atlas.

IIOAB JOURNAL
ISSN: 0976-3104

RESULTS

Shown in [Fig. 1] is the hippocampal area from the brain images from different view,(coronal view, sagittal view and axial view) for ad patients from MR images. And [Fig. 2] displays the five hippocampal subfield segmentation with atlas color mapped. [Fig. 3] shows the process of creating a surface atlas of the subfield. Below we briefly discuss about the three categories, which is age and gender for surface signals. In this experiment, we have used a three-stage pipeline model. MRI scan Subfield information is extracted, hippocampus segmentation and spherical harmonic basis functions is used for hippocampus surface modeling and calculating the mean surface.

Table 2 shows the surface vertices for five various analyses obtained from adnidatasets such as CA1, CA2-3, CA4-DG, SUB and Tail. Below table, we briefly discussed about three categories from original surface signals.(I) EMCI vsHC. There was no change in both regions and entire surface. (II) LMCI vs HC :some changes in these atrophy patterns .the pattern of the tail is 26%,SUB is 43%, CA4-DG is 30%, CA2-3 is 33%, and CA1 is 28.(III)AD vs HC shows changes atrophy pattern in of tail is 52%, SUB is 56% , CA4-DG is 32%, CA2-3 is 31% and CA1 is 90%, while subiculum is the top most region and important regions at both AD stages and LMCI stages. Age is affected 39% of CA1, 83% OF subiculum, 39% of CA2-3, and 38% of CA4-DG and tail affected 50- 57%. The entire pattern was same diagnostic method of AD stages and LMCI stages. Regarding the gender, 45-60% of CAI and Tail part, 13-15% of CA2-3, Subiculum was affected is 13-15%, and finally CA4-DG is affected 5%.

DISCUSSION

In this approach, we have presented the analysis ofsurface-based morphometric of hippocampal subfield volumetry in Alzheimer's Disease and MCI. We also used 1.5T and 3Tscans to segment the hippocampal volume and we have identified that early stages of AD and compared with the mid-term stages of MCI patients. The major three strength follows in this apprach (1) we analyzed subfield of hippocampal size (2) most important and hippocampal subfield information (3)and MR image scans with weighted images from ADNI datasets for our proposed approach. We have identified the most dominant region like subiculum and pre-subiculum. The SUB part merged into SUBICULUM and PRE-SUBICULUM, Which is a top region of AD stages and LMCI stages, after controlling the gender and age of AD patients. But the remaining region of CA4-DG and CA1 is the prudent atrophy at the LMCI stage and serious atrophy at the stage of AD. Within this control DG-CA4 and CA1 automatically reduced with increasing the age of AD patients. Volume loss of CA1 and pre-subiculum and subiculum patients in AD has been noted[22][23].another sub region of volume loss of CA4 & DG patients in AD has been noted[24][25]. And volume loss of CA3 region not yet reported till now. Moreover some hippocampal region has been combined together and reported some vivo studies For example CA3, DG & CA2. In our approach we separately identified both CA4 and CA3&DG.

The proposed surface-based analysis shows better accuracy and better diagnosis of the patients with AD and MCI diseases compared to the existing method.

Table 2: FIVE different subfield information and their analysis for existing and proposed method. (The SUB part merged into SUBICULUM and PRE- SUBICULUM.)

	Hemisphere		Left					Right				
Existing Method	Hippocampal subfields		CA1	CA2-3	CA4-DG	SUB	Tail	CA1	CA2-3	CA4-DG	SUB	Tail
	Number of vertices		389	728	91	956	398	362	735	119	941	405
	Regions	EMCI vs HC	0	0	0	0	0	0	0	0	0	0
		LMCI vs HC	135	236	33	550	89	151	210	35	494	112
		AD vs HC	195	346	52	803	223	307	365	110	762	193
Proposed Method	Hippocampal subfields		CA1	CA2-3	CA4-DG	SUB	Tail	CA1	CA2-3	CA4-DG	SUB	Tail
	Number of vertices		380	721	92	920	398	340	730	114	932	406
	Regions	EMCI vs HC	0	0	0	0	0	0	0	0	0	0
		LMCI vs HC	130	231	27	440	70	120	210	34	481	110
		AD vs HC	340	325	77	821	221	225	370	28	746	93

CONCLUSION

In this work, the surface atlas is created using free surfer and FIRST from sMRI. We have modeled a novel subfield segmentation pipeline which consists of three stages which are Subfield information extraction from MRI scan, hippocampus subfield segmentation and hippocampus surface modeling. Those are successfully surface based morphometric analyzed the AD disease with health control (HC). For the experiment, we have considered the ADNI dataset that comprises of the proposed approach. Thus it is proved that our model provides high accuracy than the other models comparatively for diagnosing the disease. The future enhancement of our work can be carried out as a robust model that can incorporate 3D hippocampal structure.

CONFLICT OF INTEREST
None

ACKNOWLEDGEMENTS
None

FINANCIAL DISCLOSURE
None

REFERENCES

[1] Alzheimer Association. [2016] 2016 Alzheimer's Disease Facts and Figures, Alzheimer's Dement. 2016, 12(4): 1–80,

[2] Weder ND, Aziz R, Wilkins K, Tampi RR. [2007] Frontotemporal Dementias: A Review, Ann. Gen. Psychiatry, 6(1): 15

[3] ILL CBB, Muller SG. [2012] Evidence for functional specialization of hippocampal subfields detected by MR subfield volumetry on high resolution images at 4T, Neuroimage, 56(3): 851–857, 2012.

[4] West MJ, Kawas CH, Stewart WF, Rudow GL. Troncoso JC, [2004] Hippocampal neurons in pre-clinical Alzheimer's disease, Neurobiol. Aging, 25(9): 1205–1212

[5] Bartsch J. Dohring A. Jansen RO, Deuschl G. [2011] CA1 neurons in the human hippocampus are critical for autobiographical memory, mental time travel, and autonoetic consciousness. Proc Natl Acad Sci, 108 (42): 17562–17567.

[6] Rössler R. Zarski J. Bohl A, Ohm TG. [2002] Stage-dependent and sector-specific neuronal loss in hippocampus during alzheimer's disease. Acta Neuropathol. 103(4): 363–369.

[7] B. Patenaude S, Smith M, Kennedy D, Jenkinson M. [2011] A Bayesian model of shape and appearance for subcortical brain segmentation. Neuroimage. 56(3): 907–922.

[8] Luders E. et al. [2014] NIH Public Access, 34(12):3369–3375.

[9] Kang DW, Lim HK, Joo SH, et al. [2018] The association between hippocampal subfield volumes and education in cognitively normal older adults and amnestic mild cognitive impairment patients. Neuropsychiatr. Dis Treat, 14: 143–152.

[10] Bartel F, Vrenken H, Bijma F, et al. [2017] Regional analysis of volumes and reproducibilities of automatic and manual hippocampal segmentations. PLoS One, 12(2): 1–19.

[11] Yushkevich PAJ. [2015] Automated Volumetry and Regional Thickness Analysis of Hippocampal Subfields and Medial Temporal Cortical Structures in Mild Cognitive Impairment," Hum. Brain Mapp, 6(1): 258–287.

[12] Krogsrud KS, et al. [2014] Development of hippocampal subfield volumes from 4 to 22 years. Hum. Brain Mapp, 35(11): 5646–5657.

[13] La Joie R, et al. [2013] Hippocampal subfield volumetry in mild cognitive impairment, Alzheimer's disease and semantic dementia. NeuroImage Clin, 3:155–162.

[14] Wisse LEM, et al. [2014] Hippocampal subfield volumes at 7T in early Alzheimer's disease and normal aging. Neurobiol. Aging, 35(9): 2039–2045.

[15] Manuscript A, Structures T. [2009] In vivo analysis of hippocampal subfield atrophy in mild cognitive impairment via semi-automatic segmentation of T2- Weighted MRI. J Alzheimers Dis. 6(1): 247–253.

[16] Son D, et al. [2010] Comparison of Manual and Automated Determination of Hippocampal Volumes in MCI and Early AD. Brain Imaging Behav, 86(3): 86–95.

[17] Cong S, et al. [2015] Surface-Based Morphometric Analysis of Hippocampal Subfields in Mild Cognitive Impairment and Alzheimer's Disease. Conf. Proc. (Midwest. Symp. Circuits Syst), 2015.

[18] Prince M, Jackson J. [2009] World Alzheimer Report 2009. Alzheimer's Dis Int, 1–96.

[19] Alzheimer's Association. [2014] 2014 Alzheimer's Disease Facts and Figures. Alzheimer's Dement, 10(2): 1–80.

[20] Ribeiro AS, et al. [2014] Multimodal imaging brain connectivity analysis (MIBCA) toolbox: preliminary application to Alzheimer ' s disease. EJNMMI Phys, 1(Suppl 1): A61.

[21] Shen L, Chung MK. [2006] Large-scale modeling of parametric surfaces using spherical harmonics. Proc. - Third Int. Symp. 3D Data Process. Vis. Transm. 3DPVT 2006, 294–301.

[22] Šimić G, et al. [1997] Volume and number of neurons of the human hippocampal formation in normal aging and Alzheimer's disease. J Comp Neurol, 379(4):482–494.

[23] Mueller SG, et al. [2010] Hippocampal atrophy patterns in mild cognitive impairment and alzheimer's disease. Hum Brain Mapp, 31(9): 1339–1347.

[24] Augustinack JC, et al. [2012] Entorhinal verrucae geometry is coincident and correlates with Alzheimer's lesions: A combined neuropathology and high-resolution ex vivo MRI analysis. Acta Neuropathol. 123(1): 85–96.

[25] Nelson EE, Guyer AE. [2012] Hippocampal CA1 apical neuropil atrophy and memory performance in Alzheimer's disease. Neuroimage, 1(3): 233–245.

ARTICLE

STUDY OF CHANGES IN THE SURFACE LAYER OF THE MEMBRANE UNDER THE EFFECT OF MICROWAVE RADIATION

Dinar D Fazullin[1], Nikita M Novikov[1*], Aisilu M Gimadieva[1], Ilnar A Nasyrov[1], Stanislav V Dvoryak[2]

[1]Department of Chemistry and Ecology, Kazan Federal University, RUSSIA

[2]Department of Physical Chemistry, Lomonosov Moscow State University, RUSSIA

ISSN 0976-3104

ABSTRACT

Studies of the surface layer of membranes have been carried out using FTIR spectroscopy, scanning electron microscopy, NMR analysis, chromatography-mass spectrometry and other methods to identify changes in the properties of membranes processed in various physical media. The processing by microwave radiation in air leads to a loss of mass of the membranes due to the etching of the surface layer. With an increase in processing time in air up to 60 minutes, the water capacity of the nylon membrane decreases from 79% to 70.4%. Nylon 66 is usually characterized by absorption bands within the range of 650–3500 cm –1, which correspond to a peptide bond. An increase in the intensity of the absorption bands within the entire range of 650–3500 cm–1 of IR spectra after the membrane was treated by microwave radiation in air was established. New absorption bands of 2340 and 2358 cm -1 were also found, what can be attributed to the vibrations of the bonds in the amine salts R 2 C = NH + - or the diazonium salts –N 2 +.Changes in the composition of the membrane, identified by IR spectrometric studies, is associated with oxidation of atomic nitrogen contained in the air. An increase in the pore size in some areas of the membrane to 2 μm after treatment with microwave radiation in air is revealed. The increase in membrane pores is also confirmed by an increase in the specific performance of the membranes.

KEY WORDS
Surface layer of membranes, pores, FTIR

Received: 14 Dec 2018
Accepted: 26 Jan 2019
Published: 10 Feb 2019

***Corresponding Author**
Email: novikovchem@yandex.ru
Tel.: + 8 (8552) 42-62-40

INTRODUCTION

In recent years, electromagnetic super high-frequency (UHF) range radiation has become rather widely used for processing polymeric materials [1].

To detect changes in the chemical composition, physical properties, and surface structure as a result of microwave radiation, the following methods are used: measuring the rate of mass loss (gravimetric method) [2], FTIR spectroscopy, scanning electron microscopy, NMR spectroscopy, methods for determining the wettability of the membrane surface and others [3-6].

The change in the mass of the membranes after treatment with microwave radiation characterizes the speed of the etching process. The change in the mass of the membranes is determined by the gravimetric method: they measure the mass of the membranes before and after treatment, taking into account the processing time.

To obtain data on the composition and structure of the surface layer of a polymer, IR spectroscopy methods are used. The method of IR- spectroscopy allows obtaining data on the chemical structure (group, bond) of the surface and in the surface layer before and after etching or polymerization. The use of modern devices (FTIR spectrometers) allows not only to obtain high resolution absorption bands, but also to fix concentration profiles in certain structures to a depth of 10 nm. The method allows establishing the formation of functional groups of different chemical nature or change their number (for example, structures containing nitrogen, oxygen, fluorine, chlorine and others), fix the detachment of molecules and crosslinking in the surface layer, as well as inoculating a new layer on the surface [7]. Literature data, and reference books are used for the assignment of absorption bands [8-9].

The method of electron- microscopy (SEM) which is widely used to establish the surface scanning structure of membranes [6, 10], allows obtaining important results in the study of thin polymer layers applied on a surface by microwave polymerization. Using SEM, one can confirm the fact of a change in the surface structure of membranes as a result of etching the surface, applying a new polymer layer on a substrate. The method also allows for control the presence of powdered polymer in the structure of the deposited coating. The SEM also makes it possible to record changes in the roughness profile and the supramolecular structure of polymers when they are etched by microwave radiation.

In this work, microfiltration membrane made of nylon is subjected to microwave radiation. Nylon 66 is a polyhe xamethylene adipamide which belongs to the group of synthetic polyamides. The molecular formula of nylon is: [—HN (CH 2NHOC (CH 2) 4 CO—] n. The structural formula of nylon 66 is shown in [Fig. 1].

In the crystalline regions, the nylon macromolecules have a flat zigzag conformation with the formation of hydrogen bonds with neighboring molecules between carbonyl oxygen atoms and the neighboring amide groups of hydrogen atoms. Therefore, nylon has a higher physical and mechanical properties than polyesters and polyalkenes, a higher degree of crystallinity (40-60%), and glass transition and melting temperatures.

IIOAB JOURNAL ISSN: 0976-3104

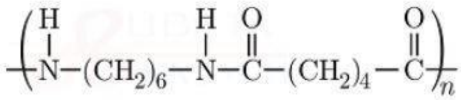


Fig. 1: The structural formula of nylon 66.

In subsequent studies, the surface layer of nylon membranes was studied using IR spectrometry and scanning electron microscopy.

In the work [6], the authors studied the effect of functionalized multi-layer carbon nanotubes of sodium dodecyl sulfate on the characteristics and performance of polyacrylonitrile (PAN) membranes. Mixed matrix membranes were obtained by mixing solutions and with the use of phase inversion methods. After acidification, the membranes then were functionalized with an amino group using microwave radiation. The resulting membranes were examined by SEM, field emission electron microscopy (FESEM), atomic force microscopy (AFM), measurement of the wetting angle with a drop of water, and FTIR spectroscopy. The hydrophilicity and

productivity as to distilled water increased with the addition of additives. The results showed that both supplements improve the performance parameters of the PAN membrane.

In [11], nylon fibers were modified with 2-acrylamido-2-methylpropanesulfonic acid (AMPS), and the polymerization was carried out using microwave radiation. The obtained nylon fibers were investigated by infrared Fourier spectroscopy, and with the use of SEM. Chromatographic properties were also studied, including permeability, and the degree of separation of proteins. The modified phase of the fiber showed an increase in the dynamic filtration rate during the polymerization by microwave radiation.

Using microwave radiation, the authors of the work [12] obtained the cation-exchange phase of nylon-COOH for ion chromatography. Polyacrylic acid was grafted onto nylon fibers by radical polymerization with microwave radiation. The surface of the obtained fibers was investigated by the method of infrared Fourier spectroscopy and SEM. The obtained IR spectra contained an absorption band of 1722.9 cm -1 corresponding to the vibrations of the –COOH group. The authors concluded that polymerization under the effect of microwave radiation has great potential as a generalized methodology for modifying the surface of polymers.

In [13], the authors modified the membrane made from nylon by microwave radiation, which was used to filter nitrogen. The radiation power was 100 Watts. The authors investigated changes in the physical properties of the surface using scanning electron microscopy. The authors found that the transmittance of nitrogen atoms is 20% after treatment of the membrane with microwave radiation for 1 minute. After increasing the processing time of microwave radiation up to 30 minutes, the transmittance of nitrogen atoms has become to 50%. According to the results of SEM studies, the authors found an increase in the pore sizes of membranes from 5 to 10 microns depending on the processing time. The results of FTIR spectroscopy confirm the formation of C-N bonds by etching the surface.

In the above work, methods of IR- FTIR spectroscopy, scanning electron microscopy, methods of NMR analysis and weight methods were used to establish the changes in the composition and properties of the surface layer of membranes, after treatment with microwave radiation. The processing of polymer membranes with microwave radiation led to an increase in the pore size, an increase in the specific productivity, a change in the wettability of the surface, and an increase in the level of crystallization of the polymer.

METHODS

To improve the performance and degree of separation of oil emulsions, we modified thin-film microfiltration membranes made of nylon by microwave radiation in the decimeter wavelength range without heat exposure using the MS-6 laboratory microwave system. During processing, the following parameters of the MS-6 installation were established: power 750–1500 W, operating frequency of 2450 MHz, temperature 24 ° C, processing time from 10 to 60 min.

A microfiltration polymer membrane of nylon with an average pore size of 0.45 μm and a diameter of 47 mm was used as the initial membrane for modification.

To assess the effect of microwave radiation on the membrane, we determined the mass of the membranes before and after treatment using an analytical balance with an accuracy of 0.00001 g.

The moisture capacity of the initial and modified membranes was determined using a brand A & MD moisture analyzer.

IIOAB JOURNAL
ISSN: 0976-3104

The study of the infrared spectra of the samples was carried out on the infrared Fourier spectrometer "InfraLUM FT-02". IR Fourier spectrometer allows obtaining a high resolution of the absorption bands. The method allows for the formation of functional groups of different chemical nature or a change in their number to identify. The reference book [10] was used to assign absorption bands.

A change in the surface structure of the membranes was recorded using a LEO-1430 VP scanning electron microscope manufactured by Carl Zeiss. The samples were glued onto aluminum plates, the surface of the membranes was sprayed with gold, using the method of cathode sputtering in argon and viewed in the high vacuum mode.

RESULTS AND DISCUSSION

The change in mass and moisture capacity of nylon membranes after microwave processing in air is presented in [Table 1].

Table 1: Membrane weight loss and moisture capacity reduction after microwave treatment in air

The name of the membrane	Processing time (min)	The decrease in the mass of the membrane Δ,%	Moisture content,%
Nylon	-	-	79.0
	10	0.12	76.5
	30	0.25	73.7
	60	0.33	70.4

After 10 minutes of membrane treatment with microwave radiation in an ammonia vapor medium, the weight of nylon membranes has decreased by 0.12% of the initial mass, and with an increase in processing time up to 60 minutes the membrane weight decreases by 0.33%. With an increase in the processing time of microwave radiation, the water capacity of the nylon membrane decreases from 79% to 70.4%.

[Fig. 2] shows the infrared absorption spectra of the original and processed by microwave radiation in an atmosphere of air nylon membrane.

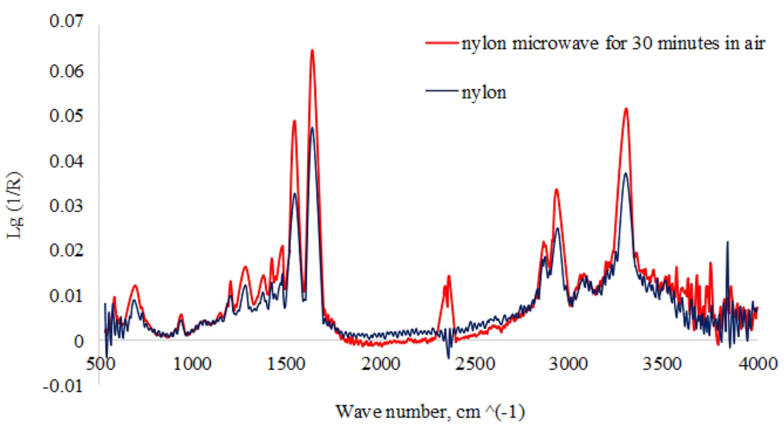


Fig. 2: IR absorption spectra of nylon before and after treatment with microwave radiation in an air environment for 30 minutes.

Nylon 66 absorption bands within the range of 650–3500 cm – 1, corresponding to a peptide bond. The absorption bands of 680 cm -1 , 726 cm -1 , 935 cm -1 correspond to out-of-plane deformation vibrations of the 2.5-substituted C – H bonds. The region of the absorption bands of 1200–1274 cm –1 refers to the vibrations of C – O bond. The absorption bands of 1370 cm -1 , 1475 cm -1 , 2855 cm -1 , 2869 cm -1 correspond to the vibrations of –CH 2 - bond , the absorption band with a wave number of 1640 cm–1 characterizes the deformation vibrations of the carbonyl group, and the 1540 cm –1 band characterizes the deformation vibrations of the N – H bond. The absorption band characterized by a wavenumber of 3050 cm -1 is associated with the deformation vibrations of the N – H bond of the secondary amide, and the absorption band of 3300 cm –1 refers to the stretching vibrations of the N – H bond of the secondary amines R2NH. These absorption bands are also present in the spectra of other compounds containing secondary amide groups, such as proteins, but other bands in the absorption spectrum of nylon 66 are specific only for this class of polymers, which makes it possible to identify them [14].

IIOAB JOURNAL
ISSN: 0976-3104

After processing the nylon membrane for 30 min in air, an increase in the intensity of the IR spectra is observed in the entire range of the absorption bands of 650–3500 cm – 1. New absorption bands of 2340 and 2358 cm -1 also appear that can be attributed to the vibrations of the bonds of the amine salts R 2 C = NH + -, or the diazonium salts –N 2 + [15].

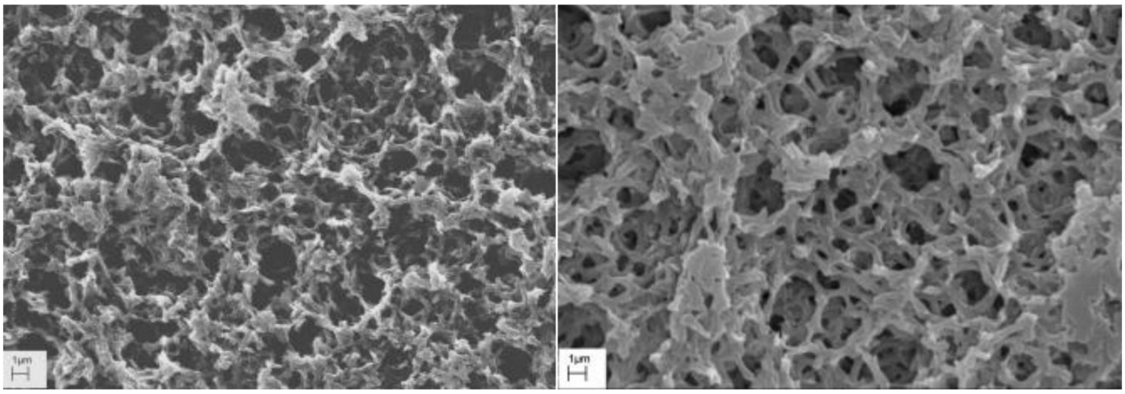


Fig. 3: Image of the surface of the original (left) and microwave treated in air (right) membrane with 3000x magnification.

Images of the original surface and the surface modified by microwave radiation in the air environment for the membranes with 3000x magnification obtained by electron-scanning microscopy are presented in [Fig. 3].

As it follows from the above photographs, the morphology of the original membrane surface undergoes changes after being treated with microwave radiation in air. If the initial membrane ([Fig. 3], left) is a set of pores with sizes from 0.2 to 1 μm, then after modification, the stuck and melted areas could be observed on the membrane surface ([Fig. 3], right). It is also seen from the figures that the pore size in some areas of the membrane after treatment increased to 2 microns.

The processing of microwave radiation in air leads to a loss of mass of the membranes; when processing a membrane made of nylon for 60 minutes, the loss of mass is 0.33%. The mass of the membrane is reduced by etching the surface layer.

The etching rate of the membrane surface depends on the nature and degree of crystallization of the polymer: the etching rate of the amorphous regions is higher, this is due to lower density and greater diffusion of the reaction gases.

With an increase in processing time up to 60 minutes in air, the water capacity of the nylon membrane decreases from 79% to 70.4% when processed within 60 minutes. The decrease in moisture capacity of the nylon membrane as a result of processing is associated with crystallization of the polymer.

An increase in the intensity of the absorption bands in the entire range of 650– 3500 cm – 1 of IR spectra after the membrane has been treated with microwave radiation in air is associated with etching the surface and destroying the defective areas of the surface layer and pores of the membrane. New absorption bands of 2340 and 2358 cm -1 also appear, what can be attributed to vibrations of the bonds in amine salts, R 2 C = NH + -. Either the appearance of these bands in the IR spectrum is associated with the formation of diazonium salts –N 2 +. Changes in the composition of the membrane identified by IR spectrometry studies are associated with oxidation by atomic nitrogen contained in the air.

After processing the microwave radiation of a nylon membrane surface ([Fig. 2], right), stuck together and melted areas are observed. It is also seen from the figures that the pore size in some areas of the membrane has increased after processing. The increase in membrane pores is also confirmed by an increase in the specific performance of the membranes.

CONCLUSION

The results of the study of membrane surfaces by FTIR spectroscopy and electron microscopy showed that as a result of microwave treatment in atmospheric air for 30 minutes, changes are observed in the surface layer of the membranes. The intensity of all the bands within the IR spectrum of the treated membrane increases, and after the treatment, new absorption bands appear that belong to the nitrogen-containing groups. Melted areas on the membrane surface and an increase in the pore size up to 2 μm are observed; that leads to an increase in the specific productivity of the membranes.

ISSN: 0976-3104

CONFLICT OF INTEREST

There is no conflict of interest.

ACKNOWLEDGEMENTS

The work is performed according to the Russian Government Program of Competitive Growth of Kazan Federal University.

FINANCIAL DISCLOSURE

None

REFERENCES

[1] Abutalipova EM, Streltsov OB, Pavlova IV, Gulmaliev EA. [2016] The study of the influence of electromagnetic radiation energy within microwave range on the structure and properties of polymeric insulating materials. Oil and gas chemistry, 4:51-55.

[2] Ricard A. [1996] Reactive plasmas. Paris: SFV. 180.

[3] Fazullin DD, Mavrin GV, Shaikhiev IG. [2016] Separation of oil products from aqueous emulsion sewage using a modified nylon–polyaniline membrane. Petroleum Chemistry, 56(5):454-458.

[4] Fazullin DD, Mavrin GV, Shaikhiev IG. [2017] Modified PTFE–PANI Membranes for the Recovery of Oil Products from Aqueous Oil Emulsions. Petroleum Chemistry, 57:(2):165–171.

[5] Fazullin DD, Mavrin GV, Nasyrov IA. [2017] Dyanamic membranes of nylon-PTEF for separation of water-oil emulsions. Journal of Fundamental and Applied Sciences, 9(1S):1441-1449.

[6] Dastbaz, Zahra, Pakizeh, Majid, Namvar-Mahboub Mahdieh. [2016] The effect of functionalized MWCNT and SDS on the characteristic and performance of PAN ultrafiltration membrane. Authors: Desalination and Water Treatment, 57 Release: 1 P.: 24267-24277.

[7] Nitscke M, Meichsner J. [1997] Low-pressure plasma polymer modification from the FTIR point of view, J of Appl Polym. Sci. 65(2):381–390.

[8] Harrick NJ, Beckmann KH. [1974] Internal Reflection Spectroscopy. In: Kane P.F., Larrabee G.B. (eds) Characterization of Solid Surfaces. Springer, Boston, MA.

[9] Lin-Vien D, Colthup NB, Fately WG, Grasseli JG. [1991] The Handbook of Infrared and Raman Characteristic Frequencies of Organic Molecules. NY.: Academic Press.

[10] [1964] Modern developments in electron microscopy. Ed. by BM Siegel NY. London: Academic Press.

[11] Liuwei Jiang R, Marcus Kenneth. [2017] Microwave-assisted, grafting polymerization preparation of strong caution exchange nylon 6 capillary-channeled polymer fibers and their chromatographic properties. Analytica Chimica Acta, 977:52-64.

[12] Liuwei Jiang R, Marcus Kenneth. [2017] Microwave-assisted grafting polymerization modification of nylon 6 capillary-channeled polymer fibers for enhanced weak cation exchange protein separations Analytica Chimica Acta, 954:129-139.

[13] Villeger S, Sixou M, Durand J. [2006] Interaction of N atoms through a nylon membrane in nitrogen flowing post discharges. Journal of Physics D: Applied Physics, 39(17):3826-3830.

[14] Tarasevich BN. [2012] IR spectra of the main organic compounds classes. Reference book. Moscow: Moscow State University named after MV Lomonosov. 53.

[15] Nelson WE. [1979] Plastics technology based on polyamides. Edited by Malkin AYa. M.: Khimiya. 256.