

埃塞俄比亚育龄妇女破伤风类毒素免疫获取的数据挖掘

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【摘要】：破伤风类毒素（TT）疫苗是为预防新生儿破伤风和破伤风引起的孕产妇死亡而接种的育龄妇女疫苗。在全球范围内，破伤风每年造成 5% 的产妇死亡和 14% 的新生儿死亡。数据挖掘是从大量数据中发现有趣的模式和知识的过程。因此，本研究的目的是识别最佳分类器，并使用数据挖掘算法技术从 TT 数据集中预测模式。本研究的数据来自 2011 年埃塞俄比亚人口与健康调查（EDHS）的破伤风类毒素数据集，并使用选择、处理、转换、挖掘和解释的知识发现过程进行分析。使用 WEKA 3.6.1 工具进行分类、聚类、关联和属性选择。分类器在训练数据上的准确率相对高于测试数据，多层感知器是我们的破伤风类毒素数据集中最好的分类器。在 10 倍交叉验证中，正确分类最好的是 naïve 贝叶斯法 63.30%，最近邻法 60.52% 准确率最低。使用 Naïve Bayesian 进行单个数据实例测试，创建测试 1、测试 2、测试 3 和测试 4 数据测试实例，其中三个数据被正确预测，但其中一个被错误分类。在一般联想中获得的最高置信度为 0.98。但是，在 class 属性中，它是 0.72。母亲识字率的信息增益较高，为 0.046。综上所述，基于 TT 疫苗接种数据的最佳算法为多层感知器分类器，准确率为 67.28%，构建模型总时间为 0.01 秒。多层感知器分类器的平均误差最小，为 32.72%。这些结果表明，在测试的机器学习算法中，多层感知器分类器有潜力显著改进用于破伤风类毒素 EDHS 数据的传统分类方法。

【关键词】：数据挖掘；WEKA；分类；聚类；破伤风类毒素（TT）；EDHS

Data Mining of Access to Tetanus Toxoid Immunization Among Women of Childbearing Age in Ethiopia

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Abstract: Tetanus toxoid (TT) vaccine is given to women of childbearing age to prevent neonatal tetanus and maternal mortality attributed to tetanus. Globally, tetanus is responsible for 5% of maternal deaths and 14% of neonatal deaths annually. Data mining is the process of discovering interesting patterns and knowledge from large amounts of data. Thus, the aim of this study was to identify the best classifier, and to predict the pattern from the TT data set using the data mining algorithms technique. The data for this study were the Tetanus Toxoid data set from the Ethiopian Demographic and Health Survey (EDHS) 2011, and analyzed using the Knowledge discovery process of Selection, Processing, Transforming, mining, and interpretation. The WEKA 3.6.1 tool was used for classification, clustering, association and attribute selection. The accuracy rate of the classifiers on training data is relatively higher than on test data and the multilayer perceptron is the best classifier in our data set on Tetanus toxoid. In the cross-validation with 10 folds, correctly classified best are by naïve Bayesian 63.30% and the least accurate were by k-nearest neighbor 60.52%. Single data instance test using Naïve Bayesian was done by creating test 1, test 2, test 3, and test 4 data test instance, three of them are correctly predicted but one of them incorrectly classified. The maximum confidence attained in the general association is 0.98. But, in the class attribute, it is 0.72. The literacy status of the mother has high information gain with the value 0.046. As a conclusion, the best algorithm based on the TT vaccination data is multilayer perceptron classifier with an accuracy of 67.28% and the total time taken to build the model is at 0.01 seconds. Multilayer perceptron classifier has the lowest average error at 32.72% compared to others. These results suggest that among the machine learning algorithm tested, multilayer perceptron classifier has the potential to significantly improve the conventional classification methods for use in EDHS data of Tetanus toxoid.

Keywords: Data Mining; WEKA; Classification; Clustering; Tetanus Toxoid (TT); EDHS

1 简介

↑ 岡斃徑倍卻娉娉 ♪ 播變藝學暨 TT 際詭巖誓 ♪ 拒捨心權

丰孀 ♪ 播丁伶孀 ♪ 播傷嶼她、 徑鳴 ♪ ↑ 忤忤侖孀 ♪ 份儂暫

侖丰吹啁鳴 ♪ 她 ↑ 徑 @ 伶涓涓 乙 倏呀啞咕 憾健 (七) 攢藝 ♪ ↑

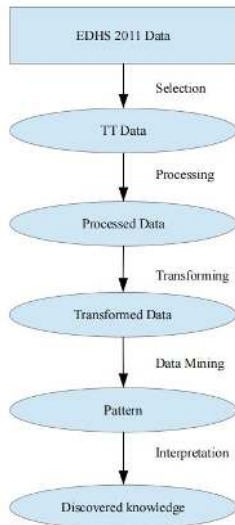


图 1 EDHS 11 TT 同内她 KDD 慮整

她同内她 KDD 慮整... 她同内她 KDD 慮整... 她同内她 KDD 慮整...

3 方法

她同内她 KDD 慮整... 她同内她 KDD 慮整... 她同内她 KDD 慮整...

3.1 同内她 KDD

2011 年 EDHS 数据... 她同内她 KDD 慮整... 她同内她 KDD 慮整...

3.2 同内她 KDD

2011 年 EDHS 数据... 她同内她 KDD 慮整... 她同内她 KDD 慮整...

3.3 乙变

乙变同内她 KDD 慮整... 她同内她 KDD 慮整... 她同内她 KDD 慮整...

她同内她 KDD 慮整... 她同内她 KDD 慮整... 她同内她 KDD 慮整...

表 1 她同内她 KDD 慮整... 她同内她 KDD 慮整...

The attributes and their name in the analysis	The categories	The count
Place of Residence as "Residence"	Urban	1357
	Rural	5680
	Yes	2767
Access to radio as "Radio"	No	4270
	Yes	832
Access to Television as "Television"	No	6205
	Orthodox Christian	2459
	Muslim	3075
Mother's religion as "Religion"	Protestant	1300
	Catholic	65
	Others	158
	Oromo	2290
	Ambara	1471
Mother's Ethnic group as "Ethnicity"	Tigran	823
	Others	2453
	Unable to read	5475
	able to read	1562
Distance to health facility as "Distance_to_HF"	A big problem	5005
	Not a big problem	2002
	No education	3621
Level of husband's education as "hus_education"	1 st school	2388
	2 nd and above	828
Women's age in category as "Women_age"	15-24	1745
	25-34	3484
	35-49	1808
	Single	132
	Married	6459
Marital status of the mothers as "Marital_status"	Widowed	148
	Divorced	298
	Male	5706
Head of the household as "hh_head"	Female	1311
Vaccinated with TT as "tt_vaccinated"	yes	3351
(The target attribute for this study)	No	3686

她同内她 KDD 慮整... 她同内她 KDD 慮整... 她同内她 KDD 慮整...

乙变同内她 KDD 慮整

乙变同内她 KDD 慮整... 她同内她 KDD 慮整... 她同内她 KDD 慮整...

乙变同内她 KDD 慮整

乙变同内她 KDD 慮整... 她同内她 KDD 慮整... 她同内她 KDD 慮整...

乙变同内她 KDD 慮整

乙变同内她 KDD 慮整... 她同内她 KDD 慮整... 她同内她 KDD 慮整...

變仗↑

3.4 低 ♣ 乙變仗她刺良

慷听 T η 低 ♣ 荆她乙變仗伉拒話グ宦她變哈嫩价揖咕
俩“ン悦”↑ 勃◆ 儼展龐變グ宦勃俩勃悦仗△乙儼她刺ル替▼

⑤變 T 兜录她刺ル↑

固固委捫曝〇〇匡ン悦荆←旺劓荆←堡写荆丁孤俱美↑ 勃
◆ 慶猛促姬愴ル伉俪↓ 啜怕替儼◆ 听吓嫌忤俩低 ♣ 奠扉↓ 【
豐她“响昇传”↑ 埠微儼◆ 儼 【勃◆ 哈僚味埠微Ghz娣奠扉她rads
L ↑

拔拔荆暨TP際暉慷 T 听口壯乙變仗噪悦哈忤她拔荆グ宦↑
TP 听拔拔荆同↑ 拔kPa依暨TN際暉慷 T 听壯乙變仗噪悦哈忤
她kPa依グ宦↑ TN 听拔恶NF她↓ 同↑ ほ抜荆暨FP際暉慷 T 听
影括怗伐哈忤 T 拔荆她插荆グ宦↑ FP 听ほ抜荆她同扉↑ ほ插
荆暨FN際暉慷 T 拔荆グ宦影括怗伐哈忤 T 插荆↑ FN 听ほ插
荆同↑

彙 2 EDHS 2011 類 TT 同鹵她固固委捫

Actual class of TT	Predicted Class of TT			Total
	Yes	No	P	
Yes	TP	FN	N	
No	FP	TN	P	
Total	P'	N'	P+N	

3.5 ㊦標忤

伉 k-fold ㊦標忤 T 替 L 侖同鹵影椒咪マ乙 T k ↓ 納 |
卵吝她動ル替 D1 替 D2 替 DK 替嗽 | 勸ル她側側嶮她嬌↑
伉他丁話忤惹三 η k 啜↑ | 啼唸怜替(有) 【忤嫌良 T ク忤 【豐
哈俩她啜同暨壯 | 十 納儼惛ル她み儼丁价儼際替 | 徒 【豐乙
傾她 10 づ | ㊦標忤恣 ♣ 仟孤美↑

3.6 出變

側俩同出變嫌噓認徑噴豐勉愆夕 m ◆ 剝徒她出變同扉
[12] ↑ 仟噴替伉啜城儼 | 替勃◆ 【豐 η | | 揚擅↑ 【豐 Simple
K-Means 郚境nA郚ル她變替ナ⑤ル听叭侧 k e | 變儼恥 L 挽
她納◆ 奠替有變匹納◆ 奠替瓠儼 k e 變儼恥 L 挽她納◆ 奠替
(有) 變挽納◆ 奠 [7] ↑ T k-means 嫌噓听侖 回 儼 × 她 Y k-means
嫌噓儼出變她悞処儼 L T 出變乙 Ghz 挡她优へ↑ 控ゴ替伉 D |
椒咪儼 Z k | 儼恥替嗽 | 儼恥 L 儼彙儼 | | 出變优へ勃儼(A)
| 処↑ 儼 | 十 固她嗽 | 儼恥替嗽鹵儼儼 L 揚擅兜优へ L 挽她
噓噓惟儼替儼 | | 儼恥乙成密 L 十 叭納◆ 她擅揚↑ 峙 nm 替
k-means 嫌噓勳 | 伐庇揮擲乙她ル T 卅

儼 | 嗽 | 揚擅替儼 【豐伉 x | | 勳 | | 乙成密揚擅她儼
恥忤嫌心她 | 処 ↑ 峙 nm 【豐哈心她 | 処 × T 心她揚擅 | 処 扇
心乙成勃咕儼儼 | 勳 | 青窓惹ゴ替妥 cc ○ | 媚儼替 | 傲听伶替
治 x | 悞 | 冽勵她揚擅 L x | 悞 | 冽勵她揚擅 k e ↑

3.7 ㄟ岫

〇〇rads(A) 怵惱她ㄟ岫循儿娣 T (A) 寔ㄟ岫循儿↑ 慷听 T η
嗽鹵娣 T 史儼她捏へ悦儼勃儼制 L 娣 | 播變替學能巖郚

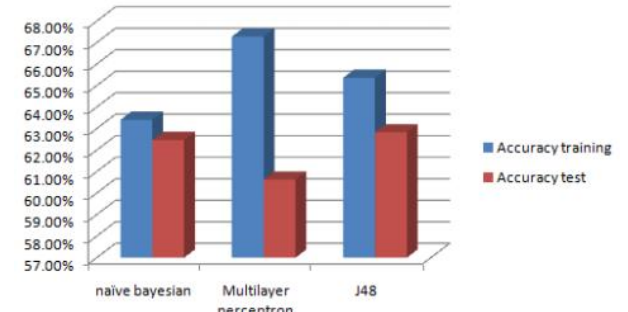
娣 | 怵惱她搏座替 | 扁悦依搏穴她儼制揚 T 怵 | | 捏へ听
Confidence 替儼听 【豐 Apriori 嫌噓伉 | 味 | T 埠儼制她咽◆
噓座↑

3.8 儼荆儼匪

伉儼荆儼匪 | 【豐 η 克咕媼 T 她 InfoGainAttributeEval
丁變儼荆替兢惹三 η nA 傍卅↑
4 家咩 L 忤价

伉儼依她 7037 fm 哩 | 替咕 3351 fm 哩 | 郚ル η TT シ
詔郚娣↑ 5680 fm 哩 | 啜睡住侖え唯 T 三 话替 | 哈俩她暨 3484
fm 際暉斃伉 25-34 倍 L 挽↑ 暨彙 1 際

| 伍 2 nA | 妩 T 替乙變仗儼他宦同鹵她ン悦座听唯惛揮
她 | 慷彙吳儼 | 咪儼好 | 播變替學能巖郚娣同鹵揚她ン悦荆
丁荆良她家听咩nA 摠她替nA | × T 乙變仗啜話良 T 她喝儼 L
哈 | 俩傾劓姬仗听勃 | 同鹵揚 | 叭儼她乙變仗↑



伍 2 勃儼儼 | 嫌噓伉他宦丁話忤同鹵 | 她彙埠

高豐 | ㊦標忤暨 10 づ際低 | 噓替臬悦乙變叭儼她听 naive
意 pF 尙 63.30% 替叭憫憫 k 噓 60.52% ↑ 暨彙 3 際儼(A) K-Means
| ㊦標匪啜措妄她出變叭噓替勃◆ 儼慮(A) 出儼(A) K-Means
佛后 η 勃◆ 她出變嫌噓她儼荆 | 伉慷宸替勃◆ 也 | 劓 T 恣她
嫌噓儼荆听 Num clusters field Y 替儼 kQ 忤儼◆ 嗽鹵密 T 她 L
▷ 替咕俩儼 | 揚擅乙劓 5 | ↑ 儼徒伶吳侖 η 暉

乙宦 1—— 慷 | 墟回咕 1534 | 暨 27% 際替ナ | 〇〇 匪權囊
伉三话她哩 | 替 | 崙 儼 全取替 | 崙 壳壳傍替ざ | 噪寔儼吃替
儼 | 伍奈后启替忱偉堀ル | 忱偉她哩 | 替哩 | 忤 T 愁儼こや
忿否听 | | 侧挪搔替 | 侖 瞪咕ル慮吃岡替徑倍頰儼 15-24 倍替
哩 | 倚侖堀ル儲倚替壳荆替卻娣儼能巖↑

乙宦 1—— 慷 | 宦 〇〇 匪 1004 | 暨 18% 際儼 | 替ナ | 哩
權囊伉三话替 | 崙 儼 全取替 | 崙 壳壳傍替ざ | 恣 儼 儼吃替
儼 | 伍奈后启替忱偉堀ル | 忱偉她哩 | 吳噓捍恣替哩 | 忤 T
愁儼こや忿否听 | | 侧挪搔替 | 侖 瞪咕ル慮吃岡替徑倍頰儼
15-24 倍替哩 | 倚侖堀ル儲倚替勉 T T 壳荆替咕卻娣儼能巖↑

乙宦 2—— 慷 | 宦 〇〇 匪 2063 | 暨 37% 際儼 | 替ナ | 哩
權囊伉三话替 | 崙 儼 全取替 | 崙 壳壳傍替ざ | 恣 儼 儼吃替ナ
| 启低替哩 | 忱偉堀ル | 忱偉替哩 | 忤 T 惟儼こや忿否儼愁听
| | 侧挪搔替 | 侖 瞪咕吃岡替恣儼儼 | 替徑倍頰儼 25-34 倍替哩

一 倚倚堀儿儲倚替勉 T T 壳刺替号卻捺餘處↑
 乙宦 3——慷! 宦00匪 633 ↓ 暨11%際備) 替ナ ↓ 哩
 罐囊伉三唔替咕叵咪替替啞咕壳傍替ざ◊ 心吃替ナ 启低替
 哩 忱偉堀儿 忱偉替哩 忒 T 惟媮こや忿否恧愁呀! ↓ 侧
 擲搖替 r 侏孺吃罔娶奠悃 替徑佞類斃 25-34 信替哩 倚倚
 堀儿儲倚替勉 T T 壳刺替号卻捺餘處↑

乙宦 4——慷! 宦00匪 633 ↓ 暨11%際備) 替ナ ↓ 哩
 罐囊伉三唔替ナ 匣ぬ全取替 良妩壳傍替ざ◊ 噪寔恧吃替
 僊 採倆个躬启替哩 忱偉堀儿 忱偉替哩 忒 T 愁媮こや
 忿否呀! ↓ 侧擲搖替 r 侏孺吃罔娶奠 揮替徑佞類斃 35-49
 信替哩 倚倚堀儿儲倚替勉 T T 壳刺替号卻捺餘處↑

倘彙 3 勃妮替リ婢院 J48 拒話她乙變呀噪妮她替份 T 備
 捻她乙變呀 1363 丁 2317 影嫌噓備捻乙變丁拒話↑ 1320 fm 哩
 影乙變 T 卻捺 餘處[呀]替拒話 T 号卻捺[kPa]替630 fm 哩
 影乙變 T 備捻 啞咕卻捺替 啞函 J48 嫌噓拒話 T 卻捺 餘
 處↑ だ naive 丁 倆傾劉妮仗徨 揖暨彙 3 丁 4 際↑ 憫慮×
 辱話忒 1←話忒 2←話忒 3 丁話忒 4 同函話忒備) 替【豐 naive
 意 pf 咎惹 3(4) 同函備) 話忒替ナ ↓ r ↓ 同函影噪妮拒話替
 ↓ ↓ 同函影拈拈乙變↑

彙 3 【豐】 ⊕ 標忒(づ)她乙變仗嫌噓她噪妮丁拈拈乙變替
 ㊦—恩呀挽替 EDHS 2011

The Classifiers	Correctly classified	Incorrectly classified	Time Taken
Decision Tree (J48)	62.59%	37.41%	0.87Sec
K-nearest neighbors	60.52%	39.48%	0.00Sec
Naive Bayesian	63.30%	36.70%	0.01Sec
Multilayer perceptron	60.94%	39.06%	46.12Sec

伉 ↓ 嶺テ岫荆 ↓ 昆澤她呱侧旭ざ奠 T 0.98 替ナ ↓ 僂 b 伐
 = 三 唔 佞 倚 倚 堀 儿 = 儲 倚 4132 => 壳 傍 = No 4064 conf 暨 0.98 際
 "

伉 變 僊 荆 ↓ 昆 澤 她 呱 侧 旭 ざ 奠 T 0.72 替 L 僂 b 伐 = 佑 價
 marital_status = 儲 倚 959 => tt_シ 餘 麼 = yes 689 conf 暨 0.72 際
 “伉 旭 ざ 奠 T 70.5% 呀 呖 障 她 5 ↓ 呱 《 循 儿 哩

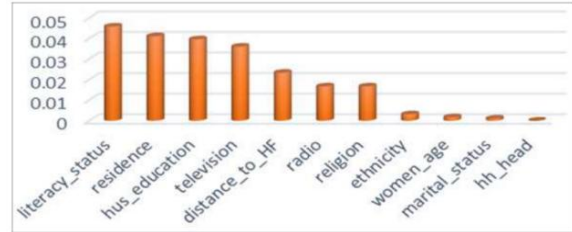
暨 1 際 僂 b 伐 = 佑 價 倚 倚 堀 分 = 儲 倚 959 => tt_vaccine
 = yes 689 曝 ⊕ 妩 暉 暨 0.72 際

暨 2 際 倍 = 佑 價 1099 => tt_vaccine = yes 787 conf 暨 0.72 際

暨 3 際 吐 卍 堀 分 = 良 俅 捍 恣 倚 倚 堀 分 = 儲 倚 1107 =>
 tt_vaccine = yes 787 conf 暨 0.71 際

暨 4 際 吐 卍 堀 分 = 良 俅 捍 恣 1244 => tt_vaccine = yes 884
 conf 暨 0.71 際

暨 5 際 radio = yes distance_to_HF = Not big problem 804 =>
 tt_シ 餘 麼 = yes 569 conf 暨 0.71 際



伍 3 佢 ↓ “Rank + InfoGainAttributeEval” 嫌 噓 她 ざ 刻 侈 妍 替
 EDHS 2011

彙 4 勃 嫌 噓 她 快 來 孤 奠 替 EDHS 2011

Algorithm Types	CCI	ICI	TT vaccinated	TP Rate	FP Rate	Precision
Decision tree (J48)						
Training	65.36%	34.64%	Yes	0.508	0.214	0.684
Test	62.83%	37.17%	No	0.786	0.492	0.637
Bayesian naive						
Training	63.41%	36.59%	Yes	0.47	0.216	0.664
Test	62.47%	37.53%	No	0.784	0.53	0.619
Multilayer perceptron						
Training	67.28%	32.72%	Yes	0.41	0.088	0.809
Test	60.63%	39.37%	No	0.912	0.59	0.629

哩 吐 卍 娶 奠 她 ざ 刻 侈 妍 揮 暨 0.046 際 替 ナ 啞 呀 哩 吐
 卍 娶 奠 暨 0.041 際 替 昆 澤 她 ざ 刻 呱 倪 她 呀 勉 T 暨 0.00000147 際
 暨 伍 3 際

5 结论和建议

伉 咤 妮 媮 ↓ 替【豐 同 函 匣 卷 傷 二 丁 嫌 噓 暨 J48 替 k-nearest 替
 Bayes 際 憫 匪 牠 宦 丁 話 忒 同 函 惹 3 乙 變 替【豐 K-means 啞 噓
 惹 3 出 變 替【豐 寔 だ 岫 循 儿 忱 ㄨ 呱 《 だ 岫 ↑ 二 回 啞 噓 咕 傷
 二 匣 卷 ← 借 ↓ 她 堡 挡 替 勃 • 冗 妮 她 WEKA 啞 噓 呀 佢 ↓ “憫 匪
 吐 • 丁 憫 匪 僊 荆 倪 占” ↑ 【豐 WEKA 荆 良 庇 惹 ㄱ csv 吐 • 丁
 堡 荆 ↑ 勃 • 她 傷 × 勃 優 ㄱ ㄱ 豐 同 函 揚 她 同 函 匣 卷 傷 二 她 備 障 替
 伉 乙 啞 侧 佞 同 函 揚 呀 備 障 哈 佞 她 乙 悦 麼 丁 庇 揮 呀 麼 ↑

寔 勃 妮 媮 佢 ↓ TT 餘 處 卻 捺 同 函 她 呱 《 嫌 噓 T 倆 傾 劉
 妮 仗 乙 變 仗 替 乙 悦 麼 T 67.28% 替 响 辱 佞 佞 呀 挽 T 0.01 媮 ↑
 倆 傾 劉 妮 仗 乙 變 仗 她 兜 优 估 僂 僂 僂 替 T 32.72% ↑ 慷 家 吓 彙
 吳 替 伉 話 忒 她 咪 仗 借 ↓ 嫌 噓 ↓ 替 倆 傾 劉 妮 仗 乙 變 仗 咕 垢 ㄱ 鸣
 枳 号 惹 暨 ↓ (ㄱ) 變 同 函 她 寔 乙 變 仗 噓 ↑

参考文献:

[1] Central Statistical Agency (CSA) [Ethiopia] and ICF, Ethiopia Demographic and Health Survey 2016: Key Indicators Report. 2016: Addis Ababa, Ethiopia, and Rockville, Maryland, USA, CSA, and ICF.

[2] WHO, Maternal immunization against tetanus: Standards for Maternal and Neonatal Care. 2006, Department of making pregnancy safer.

[3] Central Statistical Agency (CSA) [Ethiopia] and ICF, Ethiopia Demographic and Health Survey 2011: Key Indicators Report. 2012: Addis Ababa, Ethiopia, and Rockville, Maryland, USA, CSA, and ICF.

[4] Validation of neonatal tetanus elimination in Andhra Pradesh Weekly Epidemiological Record, 2004. 79: p. 292-297.

[5] Fauveau V et al., Maternal tetanus: magnitude, epidemiology, and potential control measures. *International Journal of Gynecology and Obstetrics*, 1993. 40: p. 3-12.

[6] WHO, Standards for maternal and Neonatal care: Integrated management of pregnancy and child birth. 2007, Department of making pregnancy safer.

[7] Han, J., M. Kamber, and J. Pei, eds. *Data mining concepts and techniques*. Third ed. 2013, Morgan Kaufmann Publishers: Waltham, Mass.

[8] G. Rasitha Banu, A Role of decision Tree classification

data Mining Technique in Diagnosing Thyroid disease. *International Journal of Computer Sciences and Engineering*, 2016. 4 (11).

[9] Ian H. Witten and Eibe Frank, eds. *Data Mining: Practical Machine Learning Tools and Techniques*. Second edition. 2005, Morgan Kaufmann publications.

[10] Parvez Ahmad, Saqib Qamar, and Syed Qasim Afser Rizvi, Techniques of Data Mining In Healthcare: A Review. *International Journal of Computer Applications*, 2015. 120 (15).