

Risk Management Framework to Improve Associated Risk of Information Exchange Between Users of Health Information Systems in Resource-Constrained Hospitals

Amarendar Rao Thangeda[1(✉)] and Alfred Coleman[2]

[1] Faculty of Computing, Botho University, Gaborone, Botswana
amarendar.thangeda@bothouniversity.ac.bw
[2] Department of Computer Science, University of South Africa, Pretoria, South Africa
colema@unica.ac.za

Abstract. Information exchange, privacy and security in the healthcare sector is a problem of greater significance. Healthcare Information frameworks capture, store, handle and transmit information identified with the health of the patient. However, risk management in a hospital is complex, as it includes assessing, identifying and averting risks in essentially each area of the healthcare system. In this paper, Octave Allegro based Deep Learning algorithm for a risk management framework to improve the associated risk of information exchange between users of health information systems in resource-constrained hospitals has been proposed. The experimental results show that the proposed algorithm OADLA has potential benefits for patients, organizations, health care providers, and the public during secure information exchange. The proposed Octave Allegro based Deep Learning algorithm which has higher performance when compared with existing Fuzzy based Healthcare Risk Management (FHRM).

Keywords: Risk management · Security · Privacy · Healthcare information system · Octave Allegro method · Deep learning

1 Introduction

The information Nowadays, the healthcare sector is multidimensional and competitive as any industry in the country. Risk Management in medical services involves the clinical and management frameworks, procedures, and reports utilized to identify, monitor, evaluate, mitigate, and prevent risks [1]. For utilizing Risk Management, healthcare associations proactively and methodical defend patient security just as the association's assets, brand worth, market share, accreditation, repayment levels and network standing [2, 3].

The role of risk management over hospitals, healthcare, and any other organizations is taking the approach called Enterprise Risk Management (ERM) [4]. ERM involves and encompasses eight risk domains human capital, financial, patient safety,

© Springer Nature Switzerland AG 2020
O. Gervasi et al. (Eds.): ICCSA 2020, LNCS 12254, pp. 246–260, 2020.
https://doi.org/10.1007/978-3-030-58817-5_19

operational, strategic, regulatory, technical and hazard, Fig. 1 shows the basic risk management framework [5].

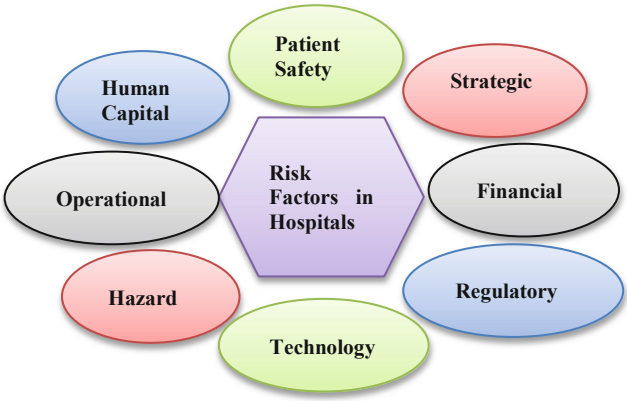

Fig. 1. Basic risk management framework.

The health information system is a framework of capture, transmit data, store the data and manage the patient's data or activities [6]. These systems are utilized to gather, process, utilize and report health data, which is used to make decisions and drive policy, research and to produce highly health outputs [7]. The key components of the HIS; resources, the management, legislation, and planning system required for framework usefulness. This incorporates workforce, financing, logistics support, information, and communication technology (ICT) [8, 9]. Markers – a total arrangement of pointers and relevant targets, including data sources, yields, and results, determinants of health, and health status indicators. Information sources – including both population-based and organization-based information sources [10, 11]. Information the board – gathering and capacity, quality assurance, preparing and streamlining, compilation and analysis [12]. Data products – information which has been investigated and displayed as actionable data scattering and use – the way toward settling on information accessible to decision-makers and encouraging the utilization of that data [13, 14].

The OCTAVE (Operationally Critical Threat, Asset, and Vulnerability Evaluation) is a security structure for deciding the risk factors and arranging verses against cyber-attacks. The system characterizes an approach to enable hospitals or health care to limit risk to likely threats, decide the possible results of an assault and manage assaults that succeed.

The OCTAVE Allegro approach gives the best quality of analysis and estimate of security information risks of a hospital. The OCTAVE approach allows to evaluate more accurately and accordingly better to decrease the risk of data security for an organization.

The correlated state of art Octave Allegro based Deep Learning algorithm (OADLA) for a risk management framework to improve the associated risk of

information exchange between users of health information systems in resource-constrained hospitals and proposed algorithm explained respectively in Sect. 3 and Sect. 4. Finally, the experimental results and conclusion discussed in Sect. 5 and Sect. 6 correspondingly.

2 Literature Survey

Richard Heeks et al. [15] introduced the Design Reality Gap Model (DRGM) for addressing the issues of health information system. They used case analysis and pilot testing of an improved model to reduce the risk and failure in the health information system. The risk assessment and mitigation on health information system is done using the design reality gap model. Determining the risk constraint in hospital and healthcare organization to predict the risk factors using the reality gap model.

WB Runciman et al. [16] suggested the method called Quadruple-loop learning (QLL) to improve the quality and safety measurements to handle the hospital and healthcare organization. They used an integrated framework for the universal patient safety classification by store, analyze and manage the data of the healthcare sector. The QLL framework can collect information from being restricted by the statement about the type of event or environment in hospital and able to be utilized by management, providers, care takers, patients, funders, and other users.

Mohamed Abomhara et al. [17] proposed the Work-Based Access Control (WBAC) model of sensitive safeguarding patient data and incorporating a risk assessment process. The access request of the risk associates identified using WBAC model and risk threshold, risk appetite against the risk of weighting to access the information or else the data will be negligible.

Claude Sicotte et al. [18] introduced the risk management system implementation using Interorganizational Clinical Information System (ICIS). The major challenges of risk associated with clinicians, IT specialists, managers, and patients or users was implemented using ICIS. The proposed taxonomy approach is to identify the risk factor or a large amount of information system security-related problem in a meaningful way to solve.

Longhua Zhang et al. [19] proposed the Role-Based Delegation Framework (RBDF) for information sharing in hospital. To reduce the risks in the healthcare sector selective information sharing is done on the basis of a role-based system. They established the feasibility of the RBDF framework through policy specification. The delegation framework includes the RDM2000 and RBAC gives a solution to the issues of handling complex access control rule set.

To overcome the above issues, in this paper, OADLA algorithm has been proposed for improving the information exchange between the health information systems in resource-constrained hospitals. The OCTAVE Allegro approach gives the best quality of analysis and estimate of security information risks of a hospital.

3 Proposed System

The Octave (Operationally Critical Threat, Asset and Vulnerability Evaluation) Allegro approach streamline improves the way towards surveying data security chances, so a healthcare sector can acquire adequate outcomes with a minimum capital in time for patients and other constrained assets. It has three main phases: (i) Create Asset and Threat based Profile (ii) Technical Vulnerabilities and assessment and (iii) Plan and Strategy Development. In phase 1, the investigation group distinguishes significant data-related resources and the present security system for the assets. The group at that point identify which of the distinguished resources are most important to the association's success, reports their protection requirement, and distinguishes threats that can interrupt with gathering requirements. In phase 2, the examination group plays out an assessment of the data framework to enhance the risk examination performed on stage 1 and in phase 3, the mitigation plan and protection strategy of the risk is being informed. The analysis group performs to recognize the actions and creates a mitigation plan for important resources. The Octave Allegro method is reducing the cost implication in the resource constrain hospital. The proposed framework that is expected to be easy to use, decreases the resource strain on the organizations, decrease training and awareness preconditions for members and the framework should fit for all sizes of the organizations(Hospitals/Healthcare institution).

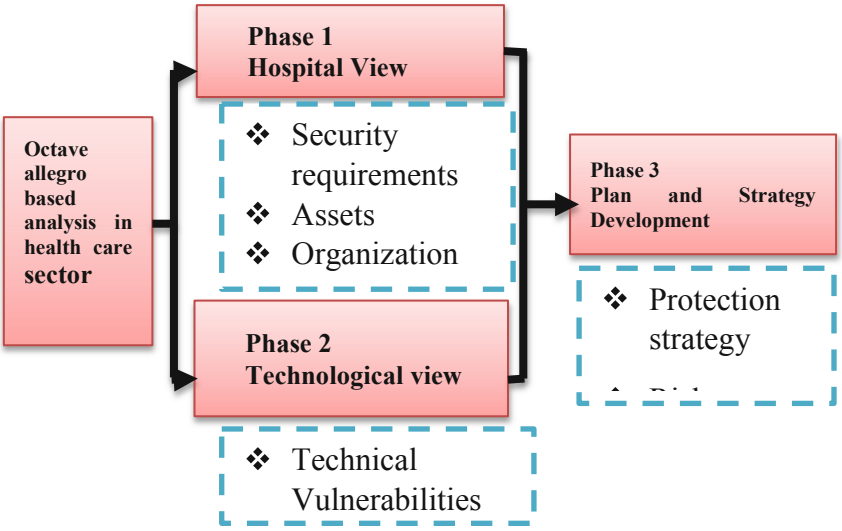

Fig. 2. The proposed Octave Allegro three-phase framework for the healthcare sector

A. Octave Allegro based on Deep Learning network algorithm

The deep learning is assisting the healthcare sector to determine the hidden information and serve better in the relating field. To make medical decisions using deep learning in healthcare provides doctors the analysis of any disease accurately and helps them to treat the patients better.

Octave Allegro based deep learning algorithm, the distribution of probability over inputs and constrained visible units and hidden units are completely connected. The higher-order visible unit denoted by u and hidden unit k_j. To reduces the overall energy in the training process the distribution data can be expressed as the following Eq. (1),

$$L(u,k) = \sum_{j=1}^{m} \sum_{i=1}^{n} E_{j,i} k_j u_i - \sum_{i=1}^{n} a_i u_i - \sum_{j=1}^{m} d_j k_j, \tag{1}$$

The model parameters indicated by $\theta = E, a, d$ and n, m are the hidden unit and visible units. The distribution of probability is stated through energy function the following Eq. (2) as,

$$S(u,k;\theta) = \frac{1}{Y(\theta)} \exp(-L(u,k;\theta)), \tag{2}$$

As shown in the Eq. (2) where $Y(\theta)$ denoted as partition function or normalized function.

The data distribution of margin through the visible unit as expressed as the following Eq. (3) is,

$$s(u,\theta) = \frac{1}{Y(\theta)} \sum_{k} \exp(-L(u,k;\theta)), \tag{3}$$

The hidden layer k_r bottom-up inference to determined attributes follows a chain rule the following Eq. (4),

$$s(k_o, k_{o-1}, \ldots, k_o|u) = s(k_o|k_{o-1}) s(k_{o-1}|k_{o-2}) \ldots s(k_1|u) \tag{4}$$

The distribution conditional of hidden unit k_t in layer t can be expressed by m units in layer r-1 as the following Eq. (5)

$$s(k_t|k_{t-1}) = \rho(a_i^t + \sum_{j=1}^{m} E_{ji}^t k_j^{t-1} \tag{5}$$

The bottom-up and top-down inference system are equal.

$$s(k_{t-1}|k_t) = \rho(b_i^{t-1} + \sum_{i=1}^{m} E_{ji}^t k_i^{t-1} \tag{6}$$

Let's consider input y, an auto encoder builds the hidden layer illustration x via definitive mapping the following Eq. (7) is,

$$x = \rho(Ez + a) \tag{7}$$

Hidden layer x is mapped back into latent illustration to rebuild y with decoder the following Eq. (8) is,

$$y = \rho(E'x + a') \tag{8}$$

Using encoder and decoder function to minimize the error between x and y. The error can be measured by cross-entropy,

$$H_L(z, y) = -\sum\nolimits_{t=1}^{v} [z_t log y_t + (1 - z_t)\log(1 - y_t)], \tag{9}$$

The data training process reduces the error reconstruction utilizes gradient decent. Therefore, the gradient descent backpropagation based on latent feature the following Eq. (10) is,

$$\varphi_{ji} = \varphi_{j,i} + \delta \frac{\partial W}{\partial \varphi_{ji}}, \tag{10}$$

As shown in the Eq. (10) where φ_{ji} is the weight, W is the weight function assess the error between prediction and target.

Chain rule has been used to calculate the loss function as expressed as the following Eq. (11) is,

$$\frac{\partial W}{\partial \varphi_{ji}} = \frac{\partial W}{\partial k_i} \frac{\partial k_i}{\partial u_j} \frac{\partial u_j}{\partial \varphi_{ji}} \tag{11}$$

The gradient descent between two layers calculates the relationship between hidden and visible layer. It is expressed basis of employing derivative on k_t

$$\frac{\partial k_i}{\partial u_j} = k_i(1 - k_i)\varphi_{ji} \tag{12}$$

As shown in the Eq. (12) where $\frac{\partial k_i}{\partial u_j}$ is a gradient function. The contribution of the hidden layer expressed as the following Eq. (13),

$$\frac{\partial q_t}{\partial u_j} = \sum_i \frac{\partial q_t}{\partial u_i} \frac{\partial k_i}{\partial u_j} = \sum_i q_t(1 - q_t)\varphi_{ti} k_i(1 - k_i)\varphi_{ji} \tag{13}$$

The latent attributes learned by deep learning to classify the performance of the deep neural network. The entropy is calculated for hidden units in one layer and evaluate the purity of the critical attributes for the nodes,

$$entrophy = \sum_{j}^{M} \sum_{i}^{D_j} \frac{B_{ji}}{B_j} log \frac{B_{ji}}{B_j}, \tag{14}$$

As shown in the Eq. (14) where M is the hidden units, the impurity can be measured using entropy for network node purity system.

Using this derivation and theory, the risk management framework is improved to reduce the associated risk of information exchange between users of health information system.

For the secure information exchange, need to identify associated risk during each stage of information exchange between the users of the hospital. The stages could be e.g. reception, medical laboratory, doctors, medical stores, one hospital to another, etc. in this paper, the proposed Octave Allegro based on deep learning algorithm illustrates the risk assessment and Fig. 3 is explained about the secure information system for healthcare divided into eight parts Authentication, Authorization, Auditing, cryptographic protection, De-identification, User Interaction, Dispute Resolution, Security Metrics.

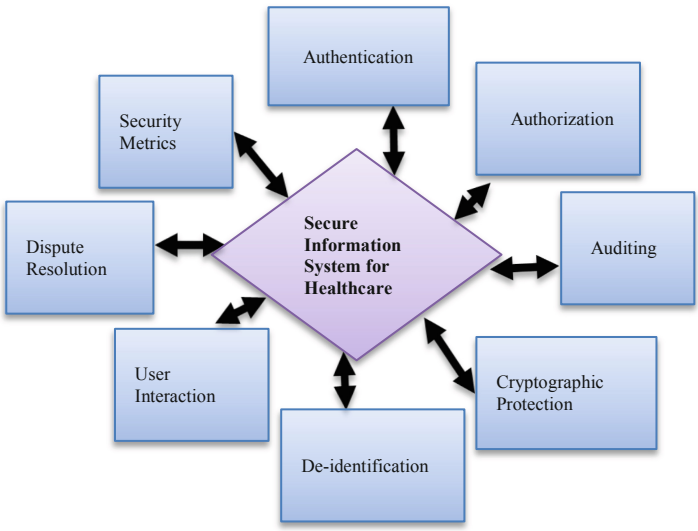

Fig. 3. Basic structure of information security system for healthcare

Algorithm: Octave Allegro Based Deep Learning Algorithm for risk factors

Input: Hidden layer, Visible layer

Output: Entropy

The training process of a deep learning algorithm

for every hidden layer k_j **do**

for every input k_o **do**

calculate $\frac{\partial k_i}{\partial u_j} = k_i(1 - k_i)\varphi_{ji}$ or

$$\frac{\partial q_t}{\partial u_j} = \sum_i \frac{\partial q_t}{\partial u_i}\frac{\partial k_i}{\partial u_j} = \sum_i q_t\,(1 - q_t)\varphi_{ti}k_i(1 - k_i)\varphi_{ji}$$

find k_j

end for

Imagine the score vector of all attributes

identify the characteristics of essential attributes

end for

estimate latent feature

For each hidden layer utilizing Eq. (12) or (13), a significant score vector with the goal that can rank all the potential risks. The system of testing latent attributes is explained in Octave Allegro Based Deep Learning Algorithm. One of the upsides of utilizing OCTAVE Allegro is that it tends to be performed in a workshop-style, community-oriented setting and is reinforced with all the required direction, work-sheets, and surveys. The technique is additionally proper for use by clients who need to perform risk investigation without broad administration inclusion, control, or information.

Algorithm 2 : Deep learning rule-based algorithm

```
Input : S, target
Output: Decision Rule
 rule = {{rule Id},{rule name},{target}},
for (j  rule) do
 if  Decision Rule = not found
 else
 if (j rule Eff= false) then
 Decision Rule = false
 end if
 Decision Rule = true
 end if
 end for
 else
 not found
repeat
end if
```

In a hospital or healthcare sector transferring data of a patient's health report securely, the deep learning rule-based algorithm is a very useful technical tool to classify the information. The rule-based deep learning methodologies incorporate learning classifier systems, affiliation rule learning, artificial immune systems and whatever other strategies that depend on a lot of rules, each covering relevant information. These systems are utilized to gather, process, utilize and report health data and also used to make decisions and drive policy, research and highly health outputs. Data product information which has been investigated and displayed as actionable data scattering and use the way toward settling on information accessible to decision-makers and encouraging the utilization of that data. The patient Id, name and description of the diseases and classify the specific data to decide the deep learning rule-based algorithm has been used.

4 Experimental Results

4.1 Performance Ratio

Deep learning is subset of the machine learning, it is a complex procedure used to improve data analysis performance. Utilizing the Octave Allegro based deep learning algorithm (OADLA) in analytic procedures provides healthcare sector risks to predict reliably. The Proposed Octave Allegro based deep learning algorithm for a risk management framework to improve associated risk of information exchange between users of health information systems in resource-constrained hospitals, performance is high when compared to the other existing methods Design Reality Gap Model (DRGM), Quadruple-loop learning (QLL), Work-Based Access Control (WBAC),

Interorganizational Clinical Information System (ICIS), Role-Based Delegation Framework (RBDF). The performance analysis is illustrated in Fig. 4.

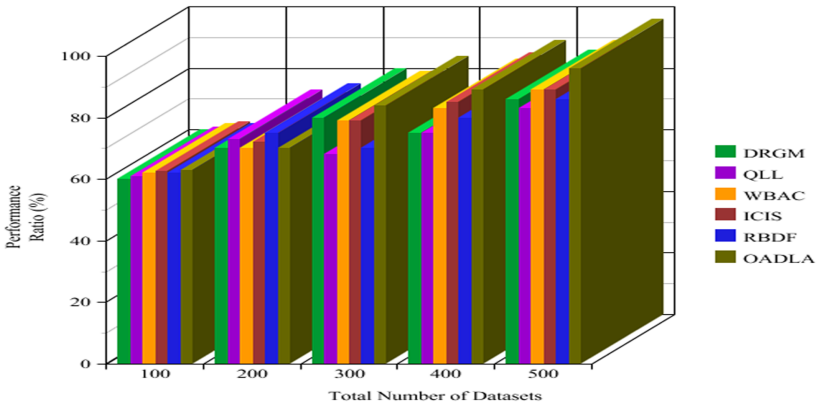

Fig. 4. Performance ratio

4.2 Accuracy Ratio

The accuracy and quality of the healthcare information security system to be identified using Octave Allegro based on deep learning algorithm (OADLA). The accuracy analysis of risk management framework to improve associated risk of information exchange between users of health information systems is high when compared to the other existing methods Design Reality Gap Model (DRGM), Quadruple-loop learning (QLL), Work-Based Access Control (WBAC), Interorganizational Clinical Information System (ICIS), Role-Based Delegation Framework (RBDF). The accuracy analysis is illustrated in Fig. 5.

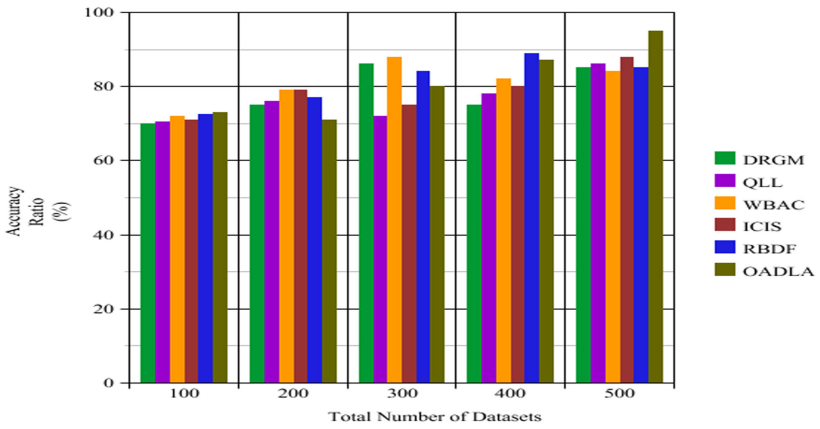

Fig. 5. Accuracy ratio

4.3 Risk Identification Ratio

Risk identification is the process of listing potential project risks and characteristics of the information security system. The Proposed Octave Allegro based deep learning algorithm (OADLA) for a risk management framework to improve associated risk of information exchange between users of health information systems in resource-constrained hospitals. Risk identification is high when compared to the other existing methods: Design Reality Gap Model (DRGM), Quadruple-loop learning (QLL), Work-Based Access Control (WBAC), Interorganizational Clinical Information System (ICIS), Role-Based Delegation Framework (RBDF). Risk Identification analysis is illustrated in Fig. 6.

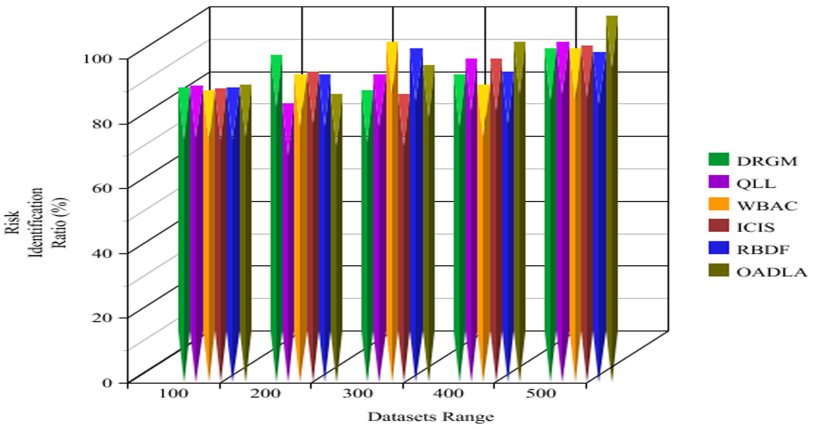

Fig. 6. Risk identification ratio

4.4 Precision Ratio

The precision rate of the proposed approach Octave Allegro based deep learning algorithm (OADLA) for a risk management framework to improve associated risk of information exchange between users of health information systems in resource-constrained hospitals precision ratio is high when compared to the other existing methods Design Reality Gap Model (DRGM), Quadruple-loop learning (QLL), Work-Based Access Control (WBAC), Interorganizational Clinical Information System (ICIS), Role-Based Delegation Framework (RBDF). The Precision ratio analysis is illustrated in Fig. 7.

4.5 Error Rate

The information exchange between the user and the healthcare sector error ratio is very complex. To decrease the error rate the proposed Octave Allegro based deep learning algorithm (OADLA) for a risk management framework to improve associated risk of information exchange between users of health information systems in resource-

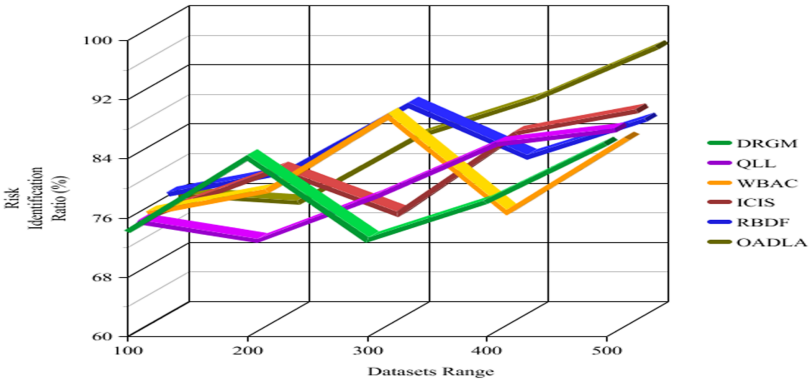

Fig. 7. Precision rate

constrained hospitals error rate is low when compared to the other existing methods Design Reality Gap Model (DRGM), Quadruple-loop learning (QLL), Work-Based Access Control (WBAC), Interorganizational Clinical Information System (ICIS), Role-Based Delegation Framework (RBDF). The error rate analysis is illustrated in Fig. 8.

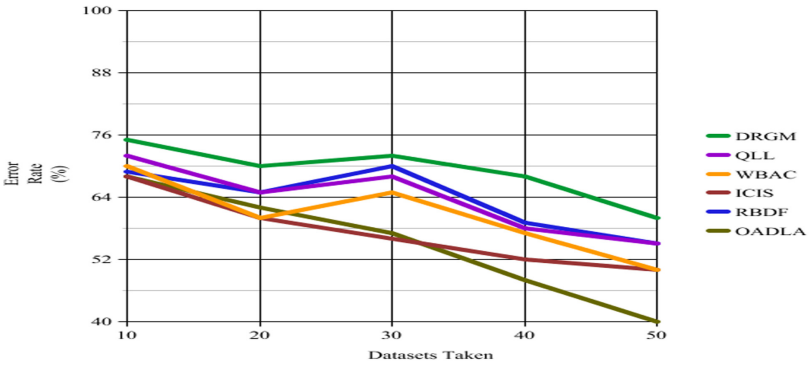

Fig. 8. Error rate

5 Comparative Analysis Between Octave Allegro Based Deep Learning Algorithm (OADLA) and Fuzzy Based Healthcare Risk Management (FHRM)

The Fig. 9 shows the Comparative Analysis between Octave Allegro based deep learning algorithm (OADLA) and Fuzzy based Healthcare Risk Management (FHRM). The OADLA algorithm which have 96% accuracy, 97% risk identification ratio, 95% precision and 98% performance ratio when compared to FHRM method.

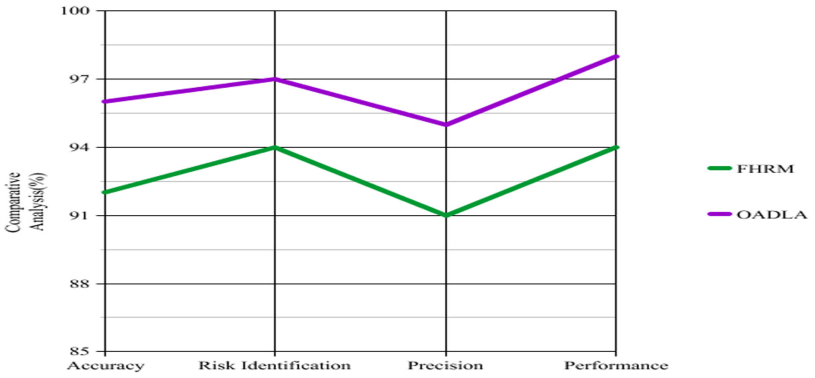

Fig. 9. Comparative analysis between OADLA and FHRM

6 Conclusion

In this paper, Octave Allegro based deep learning algorithm (OADLA) is proposed for a risk management framework to improve the associated risk of information exchange between users of health information systems in resource-constrained hospitals. Using the OCTAVE Allegro approach gives the best quality of analysis and estimate of security information risks of a hospital. The OCTAVE approach allows to evaluate more accurately and accordingly helps to decrease the risk of data security for an organization and also reducing the cost implication in the resource constrain hospital when compared to other existing methods (DRGM, QLL, WBAC, ICIS, RBDF). The experimental results and discussion section show the proposed OADLA which has better performance when compared to existing FHRM method.

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