AN INVOTATIVE DEEP LEARNING MODEL FOR GENDER-BASED CLASSIFICATION OF CANCER PATIENT

XIAOYU LI UYYANG

ABSTRACT

The advent of the Third computing platform, integrating Social, Mobility, Analytics, and Cloud (SMAC), has ushered in an era of unprecedented data generation across diverse domains like healthcare, finance, transportation, and cybersecurity. This surge in data, termed Big Data, poses challenges due to its unstructured and imbalanced nature, prompting the need for advanced analytical approaches. Deep Learning, rooted in artificial neural networks, has emerged as a powerful tool for handling the complexities of Big Data. Its ability to learn hierarchical representations of features enables it to extract intricate patterns, making it well-suited for various real-world challenges. In healthcare, for instance, Deep Learning algorithms like Neural Networks with Dropout and Random Forest have shown promise in classifying Medicare beneficiaries based on different scenarios. In one scenario, focusing on cancer-affected beneficiaries, the Deep Learning Neural Network with Dropout achieved impressive sensitivity, specificity, and accuracy scores of 99.17%, 97.68%, and 98.8%, respectively. This underscores its ability to discern complex patterns crucial for patient care. Techniques like Grid Search facilitate the identification of the most effective classifier configuration, enhancing predictive accuracy and robustness. Overall, the application of Deep Learning alongside traditional techniques offers significant promise for extracting valuable insights from Big Data across various domains.

Index Terms *Deep Learning; DLNNWD; SMAC; Random Forest, SDG.*

Reference *to this paper should be made as follows: XIAOYU LI UYYANG, (2023), "An Invotative Deep Learning Model For Gender-Based Classification Of Cancer Patient" Int. J. Electronics Engineering and Applications, Vol. 11, Issue II, pp. 12-22.*

Biographical notes:

XIAOYU LI UYYANG *was born in Hebei, China, in 1996. She received the bachelor's degree in network engineering from Hebei Normal University in 2019. She is currently pursuing the master's degree with the School of Control and Computer Engineering, North China Electric Power University in Beijing, China. Her research interest includes Artificial Intelligence and power grid operation analysis.*

1. INTRODUCTION

The evolution of computing, transitioning from mainframe to client-server architecture, and now to the SMAC era—encompassing Social, Mobility, Analytics & Cloud technologies—represents a significant paradigm shift. This convergence heralds the advent of the third computing paradigm, marked by the proliferation of diverse data sources and the emergence of Big Data. The introduction of SMAC technologies has sparked the generation of vast volumes of data from various origins, including social media platforms, mobile apps, real-time streams, smart devices, RFID chips, and the Internet of Everything (IoE). Notably, healthcare streams have made substantial contributions to this surge in data. Advancements in Information Security Management System (ISMS) standards have instilled confidence among both Cloud Service Providers (CSPs) and users, addressing security challenges associated with cloud deployment. Consequently, this has driven widespread adoption of cloud-based applications, fueled further by enhancements in web services recommendations. The convergence of SMAC technologies has facilitated seamless connectivity, exemplified by the Internet of Everything (IoE), enabling effortless connections between individuals and entities. However, the prevailing trend in this era is the exponential growth of Big Data. This data, characterized by its voluminous, fast-moving, and diverse nature, surpasses the capacities of traditional legacy systems for analysis. Thus, a paradigm shift has occurred, with a dual focus on data and computational resources. Augmented analytics, leveraging advanced techniques such as machine learning and artificial intelligence, plays a crucial role in deriving insights from Big Data.

The expansion in data size coincides with a proliferation of features, highlighting the growing significance of deep learning. Unlike conventional neural networks (NN), deep learning distinguishes itself through its utilization of hidden neurons and layers. This unique capability enables deep learning to expose unstructured data to layers, resulting in an output that represents the input data with reduced dimensionality and enhanced abstract feature extraction. Early exploration of biological neurons dates back to the late fifties, with the introduction of the perceptron by [20] for binary classification. Neurons stimulate one another, forming intricate neural networks crucial for encoding, processing, and transmitting information. The perceptron mirrors biochemical processes by transferring learning from input to output layers through activation functions. Further enhancements by [21] introduced epochs and multiple hidden layers to address complex problems, utilizing Delta rule Learning implemented via backpropagation [22] to fine-tune neuron weights for improved performance. The evolution of deep learning culminates in the creation of Deep Neural Networks (DNNs), enabled by multiple hidden layers, facilitating the development of deep architectures. However, training DNNs is pivotal to prevent gradient vanishing during backpropagation, which, although mitigated by advanced variants, may result in slower learning. DNNs offer a distinct approach to training data for supervised and unsupervised learning techniques. In unsupervised learning, data labeling is unnecessary, while supervised learning leverages weights to predict target values by minimizing training errors. Learning in DNNs is characterized by hierarchical representation, attracting researchers across diverse domains to devise cutting-edge solutions such as speech recognition, image processing, collaborative filtering, and voice-enabled services. Concepts like machine learning, overfitting, error minimization, and weight learning have been extensively explored by [33–35]. In essence, the journey of deep learning from its inception to its current state underscores its transformative potential in extracting meaningful insights from complex datasets. The utilization of hidden layers and advanced training techniques in DNNs represents a significant leap forward in addressing real-world challenges across various domains.

Due to technological limitations, the complete capabilities of Deep Neural Networks (DNNs) have not been thoroughly explored. However, with the convergence of Social, Mobility, Analytics & Cloud (SMAC) technologies, DNNs are increasingly applied in various real-world scenarios. One notable application is the pursuit of universal health coverage, identified as a global challenge within the

United Nations' Sustainable Development Goals, particularly under Goal 3 focusing on Good Health and Well-Being. The primary hurdles to achieving universal health coverage by 2030 revolve around addressing financial risks. The United States has been actively engaged in this endeavor by offering health coverage through programs like Medicare, diligently monitoring beneficiaries to detect and mitigate any potential financial risks they may face. Leveraging Medicare claims data, particularly from patients with chronic conditions, this study aims to categorize beneficiaries based on gender and cancer diagnoses. For the classification task, Deep Neural Networks (DNNs) were employed, incorporating various regularization techniques such as dropout to address overfitting concerns. The classifiers utilized include Random Forest (RF), along with Deep Learning Neural Networks with dropout (DLNNWD) and without dropout (DLNNWOD). Before classification, optimal parameters were determined through the grid search strategy.

2. MATERIALS and METHODS

2.1 Data Set

The dataset, obtained from [37], consists of Medicare claims that outline beneficiary profiles, including personal details like name, age, gender, and chronic conditions. Initially, there were several missing values in the dataset, which were dealt with using null value imputation. The chosen approach utilized maximum likelihood, which involved removing null values and then analyzing the distribution across columns. Through measures of central tendency, missing values were filled by sampling points from the distribution. Following this, significant features were identified, as explained in section 2.2.

2.2 Selection of Input Features Vectors

Figure 1 displays the 15 features derived from the profile. The other variables relate to providing enrolment details for the Medicare program, as well as averages of cost and utilization obtained from the claimed dataset. These averages are assessed and showcased separately, distinguishing between enrolment periods of equal to or less than 12 months.

Figure 1: Shows the data sets' feature descriptions.

2.3 Proposed Methodologies

The experiments were conducted separately, employing three different deep learning algorithms to classify Medicare beneficiaries under two distinct scenarios. The first scenario pertains to beneficiaries affected by cancer, while the second scenario focuses on gender-based classification, specifically targeting female beneficiaries. The methodology proposed is depicted in Figure 2.

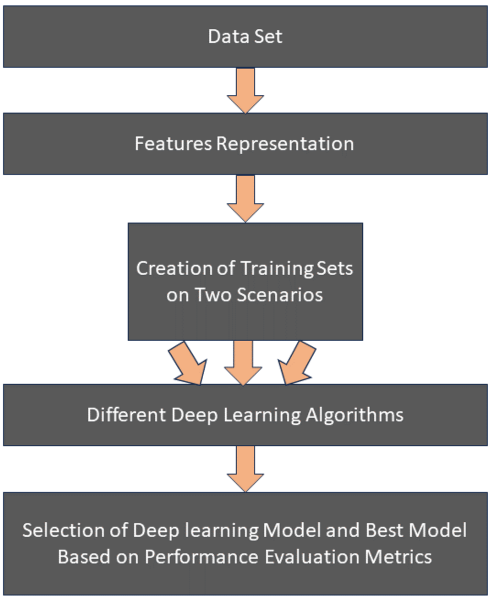

Figure 2: Proposed Methodology's Flow Diagram

2.4 Classification Protocol

In the context of classifying Medicare beneficiaries, Random Forest and Deep Learning Neural Network with Dropout were identified as the top-performing classifiers. Random Forest demonstrated superior performance in categorizing beneficiaries affected by cancer, whereas Deep Learning Neural Network with Dropout excelled in gender-based classification.

2.5 Deep Learning Algorithms

As stated in the section on suggested approaches, two scenarios were classified using three deep learning algorithms.

2.5.1 Random Forest: The learner's decision tree constituted the foundation for this ensemble learning technique. The bootstrapped instance was chosen and trained with the basic learner in the first stage. In the following phase, arbitrary examples were picked for assessment at each node. Once every instance has been trained with the basic learner, the algorithm comes to an end. The result is the combination of all the outcomes from each individual base learner. During the experiment, three hyperparameters were used: max depth, which indicates the depth to which a tree is allowed to grow, sample rate, which determines the number of samples to be produced at every split, and ntrees, which indicates the number of trees. These three hyperparameters together control the complexity of each tree.

2.5.2 Deep Learning Neural Networks: Within Deep Learning Neural Networks (DLNN), the presence of multiple hidden layers allows for the generation of more intricate features from basic ones, as highlighted in [38]. Nonetheless, DLNNs are susceptible to overfitting, a phenomenon where the model excessively learns from a specific training dataset, potentially incorporating irrelevant noise and leading to inaccurate predictions on unseen data. To counteract overfitting, it is essential to monitor both the loss and accuracy metrics on both the training and validation datasets. Common strategies to address this issue include simplifying the network architecture, implementing batch normalization, applying regularization techniques such as dropout or weight decay (L2 regularization), and employing data augmentation.

In this particular study, regularization through dropout was employed to mitigate overfitting. Dropout randomly deactivates certain activations during training, thereby reducing the model's reliance on specific weights within the network [39]. Another regularization technique, weight decay, penalizes the model's weights to encourage smaller values, ultimately aiding in mitigating overfitting [40,41]. This regularization term, known as weight decay, is introduced into the loss function E (θ) to combat overfitting, as depicted by the equation:

$$ER(\theta) = E(\theta) + \lambda\Omega(w) \qquad (1)$$

In this case, the regularization function Ω (w) is, the weight vector is w, and the regularization factor (coefficient) is λ.

$$\Omega(\mathrm{w}) = \frac{1}{2}w^T w \qquad (2)$$

The fact that the biases are not regularized must be noted [42].

The capacity of DLNN to construct higher-level features from lower-level features is one of its advantages [38]. Deep learning neural networks with and without dropout (DLNNWD and DLNNWOD)

• **The metric input_dropout_ratios:** quantifies the number of features accessible for each training sample.

• **Hidden:** Controls the dimensions and quantity of the hidden layer.

• **Regularization parameters:** These parameters address the overfitting concern, as discussed earlier. Ridge regression (L2) and L1 (Least Absolute Shrinkage Selection Operator) are utilized to normalize absolute weights and the sum of squared weights, respectively. Equations 3 and 4 depict L1 and L2 regularization applied to least-squares, respectively.

$$w^* = arg\ min \sum_j \{(t(x_j) - \sum_i w_i h_i(x_j)\}^2 + \lambda \sum_{i=1}^{k} |w_i| \quad (3)$$

$$w^* = arg\ min \sum_j \{(t(x_j) - \sum_i w_i h_i(x_j)\}^2 + \lambda \sum_{i=1}^{k} w_{i^2} \quad (4)$$

• **The parameter referred to as hidden_dropout_ratios** determines the proportion of inputs accessible for training each hidden layer.

• **Activation functions, also known as transfer functions**—Softmax, Rectifier, Maxout, and Tanh—are commonly used as activation functions for input and output hidden layers, respectively. To avoid slow convergence, the dataset undergoes training for ten epochs. The Grid Search technique, employing a random search approach, was utilized to determine the optimal values for hyperparameters. This approach ensures completion of the grid search within ten epochs. Figure 3 outlines the hyperparameters along with their corresponding values utilized in the present study.

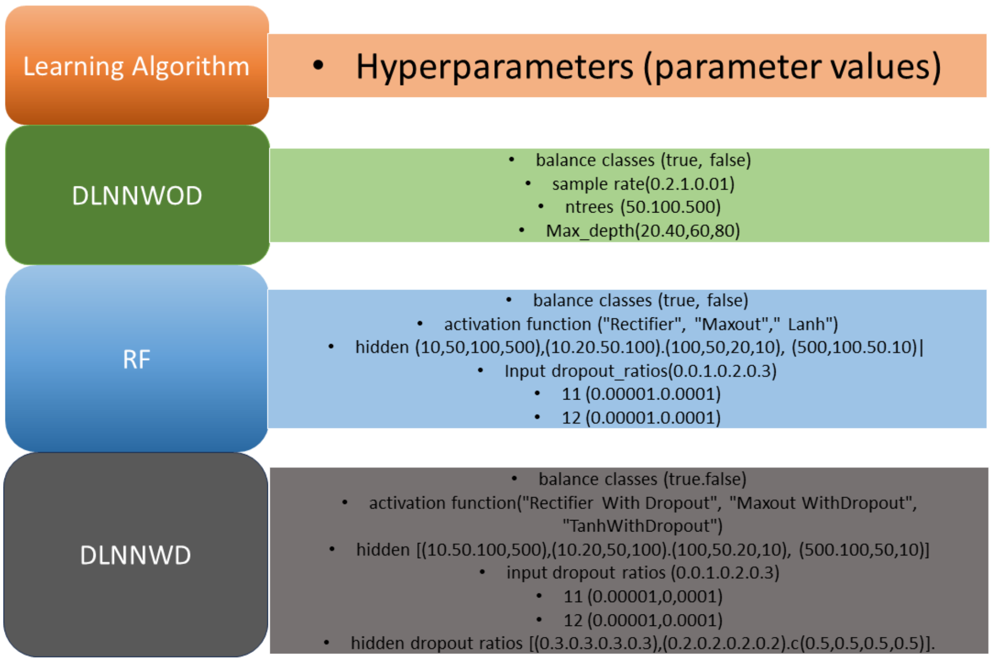

Figure 3: The adjusted hyper-parameter values

2.6 Performance Evaluation Metrics:

The classifiers' relative performances were assessed using a threshold-based evaluation. True Positives (TP) represent correctly identified cases of females or cancer patients, while False Negatives (FN) occur when patients are mistakenly labeled as having cancer or being female. True Negatives (TN) are accurately categorized as non-cancerous or involving male patients, whereas False Positives (FP) refer to cases wrongly labeled as non-cancerous or involving male patients. This evaluation framework provides a comprehensive understanding of each classifier's effectiveness in accurately classifying beneficiaries based on gender and cancer status.

Sensitivity is the accurate prediction of cases of cancer patients or female patients provided by

$$Sensitivity = \frac{TP}{(TP + FN)} \times 100 \tag{5}$$

Specificity: This is provided by and provides the ratio of accurately predicted Not Cancer/Male cases.

$$Specificity = \frac{TN}{(TN + FP)} \times 100 \tag{6}$$

Accuracy: The proportion of cases where the cancer/female and not-cancer/male predictions were made properly.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \tag{7}$$

The area under the receiver operating characteristics (ROC) is represented by the AUC [43, 44]. If the value hits 1, the classifier's prediction is most accurate.
MCC: Mathew's correlation coefficient is a commonly used performance evaluation metric that can be expressed mathematically as

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{8}$$

The geometric mean of sensitivity and specificity, or G-Means for short, is a mathematical representation of the balanced interpretation of accuracy.

$$G - Means = \sqrt{Sensitivity * Specificity} \tag{9}$$

The H2O package (45) is used to conduct the tests. In H2O, the optimizer chooses the threshold so that the F1 measure would be used to determine which models are the best.

3. RESULT and DISCUSSION

The experiment conducted involved the utilization of three distinct deep learning algorithms—Deep Learning Neural Network with Dropout (DLNNWD), Deep Learning Neural Network without Dropout, and Random Forest (RF)—on the Medicare beneficiary dataset. The performance of these algorithms was meticulously evaluated across various metrics, as outlined in Table 1. To gauge the effectiveness of the generated models, a 10-fold cross-validation approach was employed as a hyperparameter.

Dropout, an essential technique used to mitigate overfitting in neural networks, was integrated into the Deep Learning Neural Network with Dropout model. Results indicated that Random Forest (RF) outperformed other algorithms in classifying beneficiaries as cancer patients, whereas DLNNWD excelled in classifying beneficiaries based on gender. The implementation of deep learning algorithms for Medicare beneficiary classification yielded notable performance enhancements across all three algorithms.

Through rigorous experimentation with these algorithms utilizing 10-fold cross-validation, the most promising results were achieved in the first scenario, focusing on classifying beneficiaries based on cancer status. DLNNWD demonstrated exceptional performance, achieving a sensitivity of 99.17%, specificity of 97.68%, and accuracy of 98.8%. In contrast, the second scenario, which centered on gender-based classification (specifically, identifying female beneficiaries), saw RF emerge as the top performer. It achieved a sensitivity of 82.97%, specificity of 68.71%, and accuracy of 75.05%.

These findings underscore the efficacy of leveraging deep learning algorithms for Medicare beneficiary classification tasks. By harnessing the capabilities of DLNNWD and RF, significant improvements in sensitivity, specificity, and accuracy were observed, indicating their potential to enhance healthcare decision-making processes. Additionally, the utilization of 10-fold cross-validation ensured robust model evaluation and bolstered generalization capabilities.

This study emphasizes the critical role of advanced machine learning techniques in healthcare analytics. Accurate classification of beneficiaries based on attributes such as cancer status and gender contributes to improved healthcare outcomes and more effective resource allocation strategies. With ongoing research and refinement, deep learning algorithms hold promise for further advancements in healthcare analytics and decision support systems, ultimately benefiting patient care and healthcare management.

3.1 Observations on Hyperparameters -

Regarding Random Forest (RF) hyperparameters, balance class and sample_rate showed no discernible impact across both scenarios, with the number of trees remaining constant at 500 while the maximum depth varied from 30 to 53 between the scenarios.

Moving to the Deep Learning Neural Network with Dropout (DLNNWD) hyperparameters, no significant effects were observed on balance class, hidden_dropout_ratios, and input_dropout_ratios across both scenarios. However, for the first scenario, a preference for hidden parameters with consecutively lower numbers of layers was evident. Additionally, equal values for l1 and l2 regularization parameters were favored. In contrast, the second scenario favored a false balance class, with continued preference for hidden parameters with consecutively lower layer numbers. Notably, input_dropout_ratios were set to 0, while hidden_dropout_ratios with a value of 0.3 were favored. Furthermore, a preference for lower l1 values over l2 regularization parameters was observed in this scenario.

Concerning Deep Learning Neural Network without Dropout (DLNNWOD) hyperparameters, a true balance class and an input_dropout_ratios value of 0.1 were preferred in both scenarios. In the first scenario, hidden parameters were favored in increasing layer order, whereas in the second scenario, they were preferred in decreasing order. Moreover, in the first scenario, equal values for l1 and l2 were preferred, while in the second scenario, a preference for lower l1 values over l2 was evident. Additionally, Maxout activation function was favored in the first scenario, whereas Rectifier was preferred in the second scenario.

Visual representations of all classifiers in terms of receiver operating characteristics are depicted in Figures 4 and 5 providing comprehensive insights into performance metrics across various hyperparameter configurations. These visualizations serve as valuable aids for evaluating and comparing the effectiveness of different classifiers across different scenarios, aiding in informed decision-making and model selection.

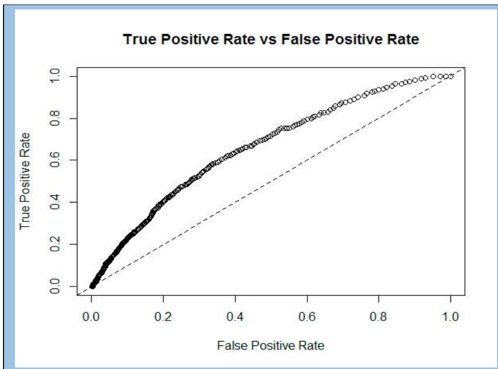

Figure 4: AUC for the gender-based DLNNWOD categorization.

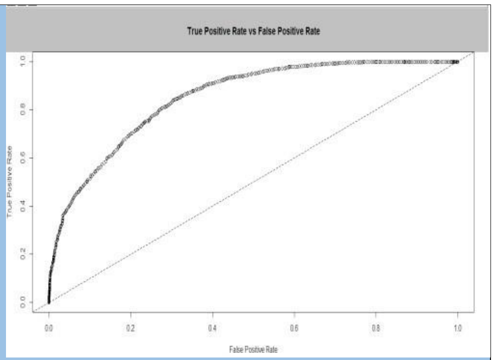

Figure 5: Shows the AUC for the gender-based RF classification.

Table 1: Presents the Performance Assessment Metrics of Deep Learning Algorithms for the categorization of Medicare Beneficiaries based on gender and cancer status.

		Classification of Medicare Beneficiaries based on being affected by Cancer			Classification of Medicare Beneficiaries based on Gender		
Learning Algorithm	Hyper Parameters	The Best Values of Hyper Parameters	Performance Evaluation Metrics	10-Fold Cross-Validation	The Best Values of Hyper Parameters	Performance Evaluation Metrics	10-Fold Cross-Validation
RF	balance_class	True	Accuracy	98.55	TRUE	Accuracy	75.05
	max_depth	30	AUC	0.9975	30	AUC	0.837
	ntrees	550	Sensitivity	98.38	550	Sensitivity	85.97
	sample_rate	1	Specificity	96.1	1	Specificity	68.71
			G-Mean	98.72		G-Mean	75.5
DLNNWOD	balance_class	True	Accuracy	96.69	TRUE	Accuracy	51.38
	hidden	[10, 50, 100, 500]	AUC	0.9931	(100,50,20,10)	AUC	0.577
	input_dropout_ratios	0	Sensitivity	98.02	0.1	Sensitivity	94.34
	l1	0.00001	Specificity	93.04	0.0001	Specificity	18.34
	l2	0.00001	G-Mean	94.04	0.00001	G-Mean	41.37
DLNNWD	balance_class	True	Accuracy	98.8	FALSE	Accuracy	62.23
	hidden_dropout_ratios	[0.3, 0.3, 0.3, 0.3]	Sensitivity	99.17	(0.3,0.3,0.3,0.3)	Sensitivity	87.47
	input_dropout_ratios	0.00	Specificity	97.68	0	Specificity	41.9
	l1	0.00001	G-Mean	98.42	0.0001	G-Mean	60.53
	l2	0.00001			0.00001		

4. CONCLUSION

The hierarchical learning process is a potent mechanism for distilling intricate features from unstructured data across multiple layers. This technique effectively reduces data dimensionality and generates higher-level feature representations. Given the extensive nature of datasets, fine-tuning hyperparameters becomes crucial to ensure accurate prediction and effective feature identification. Grid search emerges as a valuable tool in this regard, enabling the exploration of various hyperparameter combinations to optimize model performance.

In our study, we employed the grid search methodology to classify Medicare beneficiaries based on gender and cancer status. By utilizing Random Forest (RF), Deep Learning Neural Network without Dropout (DLNNWOD), and Deep Learning Neural Network with Dropout (DLNNWD) as classifiers, we aimed to determine the most effective algorithms for beneficiary classification. Our findings revealed the proficiency of these models in accurately categorizing Medicare beneficiaries, highlighting the utility of advanced machine learning techniques in healthcare analytics.

This study underscores the pivotal role of precise beneficiary information, including age, gender, and medical condition, in guiding governmental healthcare spending towards targeted interventions. By directing resources towards specific ailments, age demographics, or gender groups, policymakers can mitigate fund misuse and implement preventive measures for associated diseases. This targeted approach not only optimizes resource allocation but also enhances healthcare outcomes by addressing underlying health disparities and promoting equitable access to care.

Moreover, the developed model facilitates proactive surveillance by prioritizing claim monitoring to identify potential epidemics or localized health events promptly. By enabling timely intervention and informed decision-making, the model contributes to public health surveillance efforts and enhances healthcare system resilience in the face of emerging threats.

Despite these advancements, privacy considerations pose challenges to patient mapping within the study. Adhering to stringent privacy protocols remains essential to safeguard sensitive patient information while ensuring the validity and integrity of research findings.

Our study demonstrates the efficacy of hierarchical learning techniques and grid search methodology in classifying Medicare beneficiaries. By harnessing the power of advanced machine learning algorithms, we can optimize resource allocation, enhance disease surveillance, and improve healthcare delivery for the benefit of society.

REFERENCES

1. Oyelade O.N., Ezugwu A.E.-S. A State-of-the-Art Survey on Deep Learning Methods for Detection of Architectural Distortion From Digital Mammography. *IEEE Access.* 2020;8:148644–148676.

2. Roslidar R., Rahman A., Muharar R., Syahputra M.R., Arnia F., Syukri M., Pradhan B., Munadi K. A Review on Recent Progress in Thermal Imaging and Deep Learning Approaches for Breast Cancer Detection. *IEEE Access.* 2020;8:116176–116194.

3. Ahmed Z., Mohamed K., Zeeshan S., Dong X. Artificial Intelligence with Multi-Functional Machine Learning Platform Development for Better Healthcare and Precision Medicine. *Database.* 2020;2020:baaa010.

4. Anna A., Monika G. Splicing Mutations in Human Genetic Disorders: Examples, Detection, and Confirmation. *J. Appl. Genet.* 2018;59:253–268.

5. Samee, N.A.; Atteia, G.; Meshoul, S.; Al-Antari, M.A.; Kadah, Y.M. Deep Learning Cascaded Feature Selection Framework for Breast Cancer Classification: Hybrid CNN with Univariate-Based Approach. *Mathematics* **2022**, *10*, 3631.

6. Abunasser, B.S.; Al-Hiealy, M.R.J.; Zaqout, I.S.; Abu-Naser, S.S. Breast Cancer Detection and Classification using Deep Learning Xception Algorithm. *Int. J. Adv. Comput. Sci. Appl.* **2022**, *13*, 223–228.

7. De Fauw J, Ledsam JR, Romera-Paredes B, Nikolov S, Tomasev N, Blackwell S, et al. Clinically Applicable Deep Learning for Diagnosis and Referral in Retinal Disease. Nat Med (2018) 24(9):1342–50.

8. Chlebus G, Schenk A, Moltz JH, Van Ginneken B, Hahn HK, Meine H. Automatic Liver Tumor Segmentation in CT With Fully Convolutional Neural Networks and Object-Based Postprocessing. Sci Rep (2018) 8(1):1–7.

9. Bengio, Y., Courville, A., and Vincent, P. (2013). "Representation learning: A review and new perspectives," in IEEE Transactions on Pattern Analysis and Machine Intelligence 35, 1798–1828.

10. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., et al. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature 542, 115–118.

11. Paik S., Shak S., Tang G., Kim C., Baker J., Cronin M., Baehner F.L., Walker M.G., Watson D., Park T. A multigene assay to predict recurrence of tamoxifen-treated, node-negative breast cancer. *N. Engl. J. Med.* 2004;351:2817–2826.

12. Wang S.-Y., Dang W., Richman I., Mougalian S.S., Evans S.B., Gross C.P. Cost-effectiveness analyses of the 21-gene assay in breast cancer: Systematic review and critical appraisal. *J. Clin. Oncol.* 2018;36:1619.

13. Aljuaid, H.; Alturki, N.; Alsubaie, N.; Cavallaro, L.; Liotta, A. Computer-aided diagnosis for breast cancer classification using deep neural networks and transfer learning. *Comput. Methods Programs Biomed.* **2022**, *223*, 106951.

14. Jabeen, K.; Khan, M.A.; Alhaisoni, M.; Tariq, U.; Zhang, Y.-D.; Hamza, A.; Mickus, A.; Damaševičius, R. Breast cancer classification from ultrasound images using probability-based optimal deep learning feature fusion. *Sensors* **2022**, *22*, 807.

15. W. Wang, S. Wang, X. Ma, and J. Gong, "Recent advances in catalytic hydrogenation of carbon dioxide," *Chemical Society Reviews*, vol. 40, no. 7, pp. 3703–3727, 2011.

16. V. Roy, P. K. Shukla, A. K. Gupta, V. Goel, P. K. Shukla, and S. Shukla, "Taxonomy on EEG artifacts removal methods, issues, and healthcare applications," *Journal of Organizational and End User Computing*, vol. 33, no. 1, pp. 19–46, 2021.