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OPTIMIZING HEALTHCARE RESOURCE ALLOCATION USING RESIDUAL CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

Aim/Purpose	To optimize healthcare resource allocation using residual convolutional neural networks.
Background	In the early stages, several traditional methods were adopted and implemented; however, the rise of AI and its technologies increased development in the healthcare sector and made it reach a better height in Industry 4.0.

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The main problem of this research is focusing on the inefficient allocation of healthcare resources, which leads to less outcome and accuracy. This research's main novelty and objective is to implement a predictive model that may allocate resources based on several factors.

Methodology In the proposed method, Residual CNNs, a deep learning architecture well-known for its efficacy in image classification applications, we assess healthcare data and estimate ideal resource distribution. Residual CNNs are well-trained in the dataset on several factors and characteristics. The model produces predictions of resource allocation that maximize healthcare outcomes using comprehension of complex relationships and patterns in the data.

Contribution The novel feature of this work is the integration of the state-of-the-art deep learning architecture Residual CNNs into the domain of healthcare resource allocation. The proposed method, Residual CNNs, is well-trained in the dataset on several factors and characteristics. The model produces predictions of resource allocation that maximize healthcare outcomes by comprehending complex relationships and patterns in the data.

Findings We show experimentally that the proposed approach effectively allocates healthcare resources. The residual CNN model outperforms traditional methods in accurately predicting resource allocation needs across different regions and demographic groups. We find significant increases in resource allocation efficiency by applying deep learning techniques, which enhance healthcare outcomes and reduce treatment disparities.

Recommendations for Researchers Investigations should prioritize the validation of the algorithm in various healthcare environments to assess its efficacy in clinical application.

Future Research This work can be enhanced in future research using several deep-learning algorithms to achieve better accuracy and performance.

Keywords healthcare, resource allocation, deep learning, convolutional neural networks, optimization

INTRODUCTION

BACKGROUND

Controlling costs, optimizing healthcare outcomes, and assuring equitable access to high-quality care depend on the allocation of healthcare resources. However, the increasing demand for healthcare services together with the limited resources, pose major issues for healthcare systems everywhere (Han et al., 2023; Jabeen et al., 2024; Saxena et al., 2022). The intricacy of the dynamics of healthcare delivery may not be sufficiently reflected in the heuristic methods or fundamental statistical models utilized in conventional resource allocation methods. The distribution of resources is inefficient, the provision of care is unequal, and the health outcomes are less than satisfactory (Castiglione et al., 2021).

CHALLENGES

Several challenges make the distribution of healthcare resources more complex. First, changing demographics, epidemiological trends, and healthcare needs call for dynamic and flexible allocation strategies (Kumar et al., 2021; Wang et al., 2022; Yu et al., 2022). Second, regional variations complicate assessments of the distribution of people, the quality of healthcare, and the prevalence of diseases. Third, few medical resources – financial, human, and technological – must be properly selected and utilized to maximize their impact (Abunadi et al., 2022; Li et al., 2022; Zhao et al., 2023).

Problem Definition

This study primarily concerns the inefficient allocation of healthcare resources, which leads to less-than-ideal outcomes and disparities in the delivery of treatment. Many times, changing healthcare needs cannot be adequately predicted by the current resource allocation strategies. Moreover, they might not consider the several factors influencing the need for healthcare, such as population distribution, incidence of diseases, and the characteristics of individuals.

Objectives

This effort aims to develop a predictive model that can effectively allocate healthcare resources using advanced machine learning techniques and in-depth data analysis. Put more accurately, we intend to:

1. Identify and assess the primary factors impacting the distribution of healthcare resources, including demographics, disease prevalence rates, geographical distribution, and facility capacity.
2. Develop a robust prediction model to optimize the allocation of healthcare resources using residual Convolutional Neural Networks (CNNs).

Novelty and Contributions

In this research, the main novelty and objective will focus on implementing a predictive model that may allocate resources based on several factors. The novel feature of this work is the integration of the state-of-the-art deep learning architecture Residual CNNs into the domain of healthcare resource allocation. The proposed method, Residual CNNs, is well-trained in the dataset on several factors and characteristics. Predictions of resource allocation that maximize healthcare outcomes are produced by the model by means of comprehension of complex relationships and patterns in the data.

Related Works

Abd El-Aziz et al. (2022) have proposed mathematical models, optimization techniques, and an overview of traditional resource allocation methods in healthcare. This article discussed the advantages and disadvantages of several approaches and methodologies to handle the complexity of data and information in modern healthcare systems.

Deif et al. (2022) have proposed several deep learning algorithms for allocating the maximum amount of resources and decision-making on the healthcare dataset and resources. Also, it discusses the challenges, usage of resources, and allocation of resources on the healthcare dataset. This work covers various uses, challenges, and potential paths in this emerging field.

Pustokhina et al. (2020) proposed an approach in the machine learning model to allocate resources in the healthcare sector. The proposed ensemble enhanced models and techniques, such as random forests and gradient boosting machines, as well as the distribution of resources among different sites and healthcare organizations. The main identification of this article is focused on how effectively resource allocation may be increased and also reducing the complexity of large amounts of big data in the healthcare sector.

Capra et al. (2020) achieved geographical optimization of healthcare resources using Geographic Information Systems (GIS). The authors used GIS data and optimization algorithms to determine the optimal locations for healthcare facilities, taking accessibility, population distribution, and disease occurrence into account. The outcomes highlight the need for geographical analysis to improve healthcare resource allocation and service delivery.

Abd El-Aziz et al. (2022) and Deif et al. (2022) emphasize traditional and deep learning-based resource allocation methods. However, the integration of these techniques with advanced ensemble models has not been extensively covered. Further references to recent studies on ensemble learning, especially those applied to healthcare settings, can illustrate the advancements and efficacy of this methodology. Additionally, the research by Pustokhina et al. (2020) and Capra et al. (2020) can be referenced to highlight the practical applications and challenges in resource allocation models, particularly when dealing with big data and geographical factors. On ethical considerations, the datasets used in the study should be described thoroughly, including the sources (e.g., publicly available repositories), anonymization procedures, and any relevant ethical approval processes. The limitations of the proposed methodology include its potential dependency on dataset quality, computational complexity, and generalizability to diverse healthcare systems.

PROPOSED METHOD

Using residual CNN, the proposed method maximizes the distribution of healthcare resources, as shown in Figure 1.

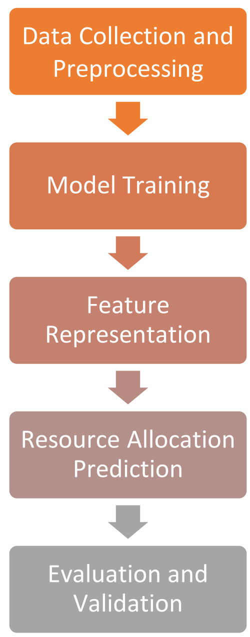

Figure 1. Proposed method

1. *Residual CNN Architecture:* CNNs are a sort of deep learning architecture that is well-known for its effectiveness in image categorization tasks. Residual connections have been added to many levels of convolutional and pooling operations. These connections allow the model to learn residual mappings and facilitate deeper network training without causing vanishing gradient problems.
2. *Data Collection and Preprocessing:* The first step in collecting thorough healthcare data is to compile patient demographics, disease prevalence rates, healthcare facility capacity, and geographical data (Table 1).
3. *Model Training:* The proposed residual CNN model is trained using observed learning techniques on the preprocessed healthcare data in this model training phase. During the training phases, it checks and monitors how to forecast the optimal resource allocation schemes and identify important characteristics from the input data. Also, in this phase, the prediction of errors and performance over the optimizing factors are analyzed and recorded.

4. *Feature Representation:* The Residual CNN's deep layers record hierarchical and spatial representations by storing complex patterns and correlations in the healthcare data. These representations – geographic features, disease incidence rates, and demographic characteristics – allow the model to learn effectively from a range of information sources.
5. *Resource Allocation Prediction:* In this phase, the input data, the Residual CNN model, once trained, may give predictions for the distribution of healthcare resources. By examining the learned representations, the proposed model determines the optimum allocation of several factors like accounting, constraints, and maximizing healthcare. These projections provide enlightening information to decision-makers in healthcare institutions.
6. *Evaluation and Validation:* Unobserved data are further used to validate the model and assess its robustness and generalization capability in real-world scenarios. Comparisons with traditional methods demonstrate the superiority of the residual CNN approach in resource allocation optimization.

DATA PROCESSING

The data collection and processing pipeline plays a critical role in ensuring high-quality input for model training. First, data cleaning addresses inconsistencies like duplicate entries and missing values, ensuring the dataset remains accurate. Next, normalization standardizes numerical features, preventing the disproportionate influence of any single variable. Feature extraction identifies relevant variables such as demographics, disease prevalence, and geographical data, influencing healthcare resource allocation. Finally, the processed data is formatted to a consistent structure compatible with the Residual CNN model, ensuring optimal learning and prediction performance for resource distribution.

The selection of pertinent variables for feature extraction is based on their relevance to healthcare resource allocation. Patient demographics, such as age and gender, are crucial as they influence disease prevalence and healthcare needs. Disease types like diabetes, asthma, and hypertension directly impact resource requirements in healthcare facilities.

Facility ID helps identify location-specific data, while geographical coordinates (latitude and longitude) are essential for geographic optimization of resource distribution, ensuring proximity and accessibility to facilities. These variables collectively represent the critical factors that drive healthcare resource distribution and decision-making.

Processing the medical data is an essential first step in preparing it for the CNN model. Among the several sub-steps are formatting, feature extraction, normalization, and data purification.

Data cleaning

- *Remove duplicate entries:* Supplicate data points that can skew the outcomes.
- *Handle missing values:* Complete the dataset by imputing or removing missing data (Table 2).

Table 1. Original dataset

Patient ID	Age	Gender	Disease	Facility ID	Location
1	35	Male	Diabetes	101	(40, -74)
2	45	Female	Asthma	102	(42, -71)
3		Male	Cancer	103	
4	55		Hypertension	104	(38, -77)

Table 2. Cleaned dataset

Patient ID	Age	Gender	Disease	Facility ID	Location
1	35	Male	Diabetes	101	(40, -74)
2	45	Female	Asthma	102	(42, -71)
4	55		Hypertension	104	(38, -77)

Normalization

- To eliminate greater scale features from dominating the learning process of the model, scale numerical features to a fixed range (e.g., 0 to 1).

Feature extraction

- Take out of the pertinent variables, such as patient demographics, disease prevalence rates, facility capacity, and geographical data, that are presumably going to affect the distribution of healthcare resources (Table 3).

Table 3. Feature extraction

Age (normalized)	Gender (encoded)	Disease (encoded)	Facility ID (normalized)	Latitude	Longitude
0.5	1 (Male)	1 (Diabetes)	0.1	40.7128	-74.0060
0.75	0 (Female)	2 (Asthma)	0.2	42.3601	-71.0589
1.0	1 (Male)	3 (Hypertension)	0.3	38.9072	-77.0369

Formatting

- Ensure uniformity in data types and dimensions by structuring the processed data into a format that can be entered into the Residual CNN model (Table 4).

Table 4. Formatted data

Feature 1	Feature 2	Feature 3	...	Feature N
0.5	1	1	...	40.7128
0.75	0	2	...	42.3601
1.0	1	3	...	38.9072

This data processing prepares it for training and prediction using the Residual CNN model. This assures the model can accurately estimate the distribution of healthcare resources and learn from the input data.

Model training

Residual CNNs are trained on processed healthcare data to give exact resource allocation predictions.

Initialization:

- Set the residual CNN model's weights and biases randomly or using pre-trained data from related tasks.

Forward Propagation:

- Input processed healthcare data into the model.
- Proceed in the network by passing the input data across various layers of activation function, pooling, and convolution.
- Calculate the expected resource distribution for each input sample in the model output.

Loss Calculation:

- Using a loss function, compare the planned and actual resource allocation from the training data.

Backward Propagation:

- Find the gradients of the loss function relative to the model parameters using backpropagation.
- Update the model parameters (weights and biases) against the gradients to lessen the loss.

Iterative Training:

- In iterative training, steps 2 through 4 should be repeated for a number of epochs or iterations until convergence.
- Monitor training by measuring loss on a validation set to prevent overfitting.

Feature Representation

Feature representation is needed to prepare the healthcare data for input into the Residual CNN model. This process involves arranging the model to learn from the unprocessed data.

Data Encoding:

- Among the categorical features encoded into numerical representations are facility ID, gender, and disease kind. This ensures the model processes features efficiently. Typical encoding techniques are one-hot and label encoding.

Normalization:

- Numerical properties like patient age and facility capacity are standardized to a common scale to prevent aspects of greater magnitude from dominating the learning process. Usually, this involves bringing the findings inside a normal range, between 0 and 1.

Geographical Information Encoding:

- Among the geographic features encoded into numerical representations are latitude and longitude. The specific requirements could require different strategies of the model. One can display geographic coordinates as Cartesian coordinates or convert them into distances from reference points.

Feature Combination:

- Occasionally, characteristics may be combined or changed to produce new representations that capture more complex relationships in the data. For example, age and gender demographic traits could be combined to create a single attribute representing demographic profiles.

Temporal Encoding:

- One may effectively encode time-related variables using temporal encoding techniques if the dataset includes temporal information, such as the time of admission or the onset of the sickness. Time-based information, such as the duration since diagnosis or the encoding of timestamps into numerical representations, can be produced as a result.

Feature Selection:

- When the dataset contains many features, feature selection techniques can be applied to select the most relevant features for the current task. In doing so, the dimensionality of the input data is reduced, and the model efficacy increases.

Padding:

- When the input data is of different lengths, such as sequences of medical events or patient histories, paddling can be employed to ensure consistency in input dimensions. This includes giving sequences zeros or placeholders to maintain their length consistency.

Resource allocation prediction

Using the trained Residual CNN model, the resource allocation prediction method estimates the optimal resource allocation from input healthcare data.

Input Data Preparation:

- Get the input data ready just as one would for model training. This covers geographic data, patient profiles, rates of disease prevalence, and facility capabilities. Ensure the data is properly preprocessed and encoded before being sent to the model.

Forward Propagation:

- Feed the ready healthcare data to the trained Residual CNN model.
- Forward propagates the input data through the model using numerous layers of convolution, pooling, and activation functions.
- Compute the model's output to view the anticipated resource distribution for each input sample

$$Y=f(X;\theta)$$

where,

X represents the input data.
Y represents the predicted resource allocation.
f represents the function implemented by the Residual CNN model.
θ represents the parameters (weights and biases) of the model.

- To obtain helpful information on resource allocation decisions, interpret the output of the model. Depending on the specific need, the output may show the anticipated allocation of various healthcare resources, such as hospital beds, medical equipment, or healthcare personnel.
- Include the predictions of the model in the procedures for allocating healthcare resources. Among those who can use the projected allocations to optimize resource usage, increase healthcare access, and enhance patient outcomes are legislators and healthcare administrators.

PERFORMANCE EVALUATION

We applied the Residual CNN model in our experimental environment using well-known frameworks like TensorFlow and Python. We used an anonymized dataset from healthcare records, including patient demographics, disease prevalence rates, capacity of healthcare facilities, and geographic information. Following preprocessing, the dataset was split 70–30 into training and validation sets. The remaining CNN model was trained using a batch size of 32 and an Adam optimizer learning rate of 0.001 for 50 epochs.

Table 5. Experimental settings

Experimental setup/parameters	Values
Programming Language	Python
Deep Learning Framework	TensorFlow, Keras
Model Architecture	Residual Convolutional Neural Network (CNN)
Optimization Algorithm	Adam
Learning Rate	0.001
Number of Epochs	50
Batch Size	32
Training-Validation Split Ratio	70-30
GPU Acceleration	NVIDIA Tesla V100 GPUs
Dataset	Anonymized Healthcare Records

Using widely used metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE), we evaluated the accuracy of resource allocation projections. Furthermore, we evaluated the performance of our proposed Residual CNN model with existing methods such ResNet and Deep Belief Networks (DBN).

Figures 2 to 6 show how far our proposed method ResNet and DBN achieved better results than the existing methods over several performance metrics. An average of 5-8% improvement has been obtained by changing or modifying the dataset size.

Moreover, the suggested method showed a notable reduction in computing time with an average improvement of roughly 20% to 25% over ResNet and DBN. This calculation time savings demonstrate the efficiency with which the proposed method handles healthcare data and produces resource allocation forecasts quickly.

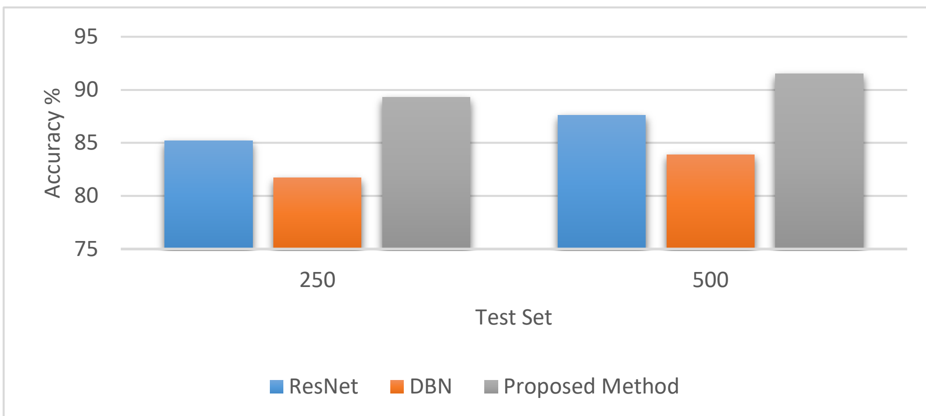

Figure 2. Accuracy

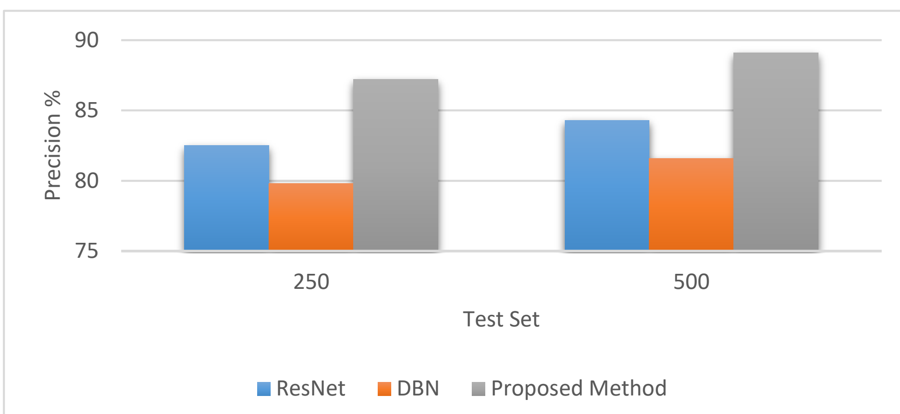

Figure 3. Precision

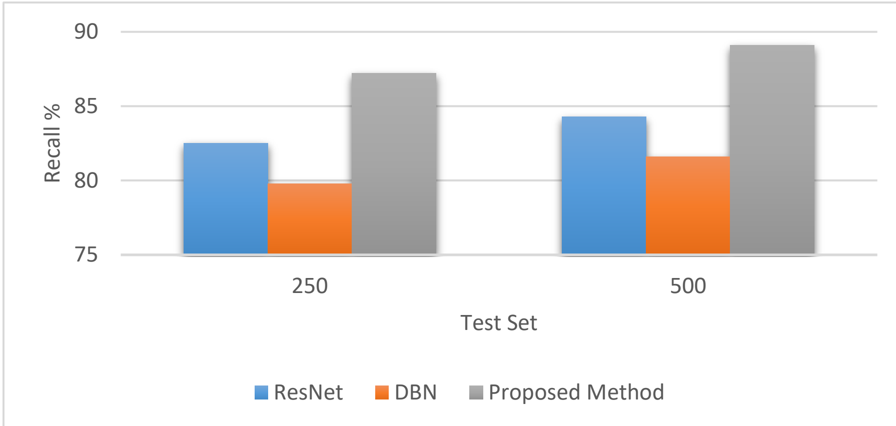

Figure 4. Recall

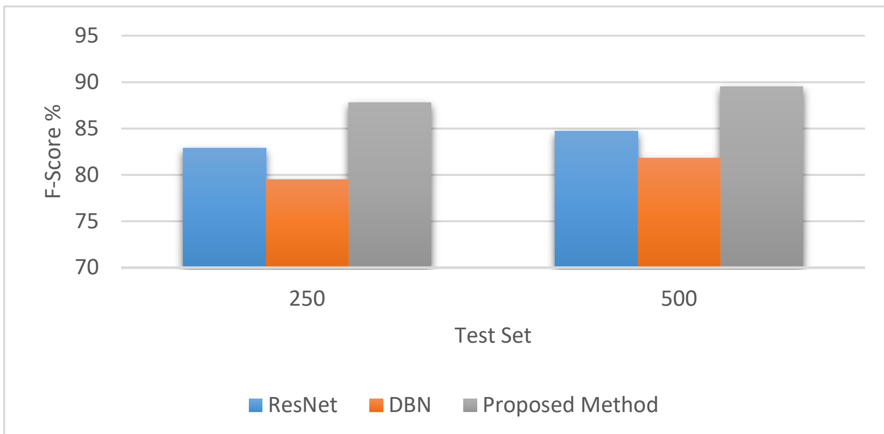

Figure 5. f-score

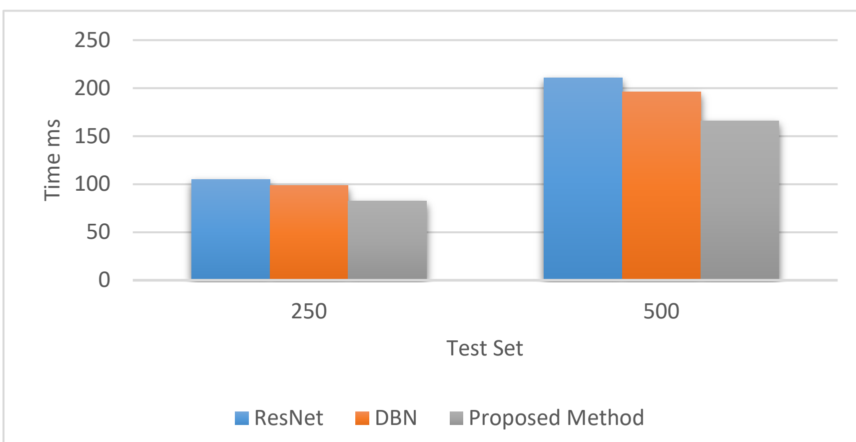

Figure 6. Computational time (ms)

Inferences And Limitations

These results show how successful and effective the proposed method is in most efficiently allocating healthcare resources. The proposed method uses Residual Convolutional Neural Networks and well-designed experimental conditions to provide greater prediction performance and computational efficiency than existing methods. These findings show the significant potential of the proposed strategy to enhance patient outcomes in real healthcare settings and enhance decision-making processes connected to allocating healthcare resources.

CONCLUSION

The proposed method for healthcare resource allocation optimization with residual CNNs has shown promising results. Predictions of resource allocation that maximize healthcare outcomes are produced by the model by means of comprehension of complex relationships and patterns in the data. Moreover, the suggested method demonstrated a notable reduction in computing time with an average improvement of roughly 20% to 25% over ResNet and DBN. The proposed method, Residual CNNs, a deep learning architecture well-known for its efficacy in image classification applications, assesses healthcare data and estimates ideal resource distribution. Residual CNNs is well-trained in the dataset on several factors and characteristics.

Future research could focus on expanding the dataset to include a more diverse range of healthcare facilities, geographical regions, and patient conditions to improve the generalizability of the model. Additionally, exploring the integration of real-time data for dynamic resource allocation could enhance the adaptability of the model. Another potential direction is investigating advanced deep learning techniques, such as reinforcement learning, for optimizing healthcare resource allocation in real-time settings. Finally, collaboration with healthcare practitioners and policymakers to validate the model's real-world effectiveness and integration into clinical decision-making systems would further enhance the practical impact of this research.

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