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ORIGINAL RESEARCH

Optimizing healthcare workforce for effective patient care: a cooperative game theory approach

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Abstract

Efficient staff allocation and workload management are critical challenges within the healthcare industry, impacting patient satisfaction and treatment timeliness. Many hospitals still rely on manual methods for patient record management and staff assignment, resulting in uneven work distribution and patient dissatisfaction due to delayed treatments. To address these pressing issues, we propose a novel Deep Learning Enhanced Shapley Values Allocation (DESVA) approach, including a cooperative game theory approach that utilizes the Shapley value concept in Deep Neural Network (DNN). This research explores the transformative potential of cooperative game theory in revolutionising healthcare staff management practices. Our approach systematically assesses patient needs and staff capabilities, fostering cooperation among healthcare team members. Through practical applications in hospital management projects, we aim to achieve equitable work allocation and enhance the overall patient experience. Within this study, we delve into the intricacies of team interactions and the role of a designated entity in healthcare staff management. Our findings underscore the proactive contributions in optimising both individual and team performance. Furthermore, we emphasize the importance of adaptive strategies within healthcare teams, acknowledging differing energy levels and effectiveness. Team members are encouraged to adopt active or passive roles as the situation demands, all while considering potential costs associated with interpersonal relations and workflow processes. This adaptive approach ensures a balanced and responsive allocation of resources. It is important to note that this research extends beyond healthcare. The insights gained from our cooperative game theory approach hold relevance for professionals and decision-makers across diverse domains. By recognizing the significance of teamwork, resource allocation, and adaptability, these insights empower professionals to identify suitable strategies for maximizing outcomes in their respective contexts. The performance of DNNs and Shapley values in DESVA is intertwined. DNNs offer the modelling prowess to capture intricate healthcare data relationships, while Shapley values measure the contributions of staff members. The efficiency and effectiveness of the proposed DESVA are ultimately showcased through rigorous simulations.

Keywords Cooperative game theory · Shapley value concept · Deep neural network · Staff management · Hospital policies · Work allocation strategy

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1 Introduction

Game theory is a decision-making theoretical framework for performing an essential role in social applications for competing players. This works on the science of strategy among multiple players to make optimal decisions. The healthcare industry must have an efficient workforce to safeguard societal health and well-being. Organising the workers and optimising the work requires advanced technology to understand. To make the perfect decision on organising the workforce, cooperative game theory supports two sides for optimal decision-making. The healthcare industry stands at the forefront of technological advancements, promising exceptional advantages in patient care and medical services. Healthcare institutions have recently witnessed remarkable progress in medical treatments, diagnostic capabilities, and patient outcomes (Lazebnik, 2023; Sasanfar et al., 2021). However, amid these advancements, the industry grapples with a critical challenge that has profound implications for healthcare providers and patients: allocating and managing staff resources. Efficient staff allocation and workload management have emerged as central tenets of healthcare delivery. The allocation of skilled professionals, such as doctors, nurses, and support staff, directly impacts the quality of patient care and the overall hospital environment (Lewis & Mulla, 2021; Li et al., 2022, 2023). Proper staff allocation ensures that healthcare facilities operate smoothly and contributes significantly to patient satisfaction and timely treatments.

In the contemporary healthcare landscape, characterised by remarkable advancements and innovations, it is paradoxical that many healthcare institutions persist in using archaic, manual methods for staff allocation and workload management (Hao et al., 2023a; Li, 2021; Wu et al., 2023). These traditional systems demand that staff members partake in labour-intensive site visits to access patient records and make crucial decisions regarding allocating staff resources. Unfortunately, this dated approach often results in a significant imbalance in work distribution and delays in providing essential medical care to patients. The repercussions of these imbalances are starkly evident: patients frequently endure prolonged wait times, and the overall effectiveness of the healthcare system becomes compromised (Hao et al., 2023b; Li et al., 2023; Xue et al., 2023). Recognising the pressing need for a transformative solution to this systemic challenge, our proposed approach emerges as a beacon of hope. Rooted in the principles of game theory and, more specifically, making adept use of the Shapley value framework, our approach seeks to revolutionise the healthcare landscape (Cai et al., 2019; Wang et al., 2018). It acknowledges the intricacies of staff allocation and workload management, aiming for a more equitable and efficient system. By harnessing the power of game theory and the Shapley value concept, we strive to ensure that every staff member's contribution is recognised and appropriately factored into the allocation process. Through this innovative approach, we envision a future where patient care is more streamlined, wait times are significantly reduced, and the healthcare system's overall effectiveness is elevated to new heights (Talaat, 2022).

In this paper, we introduce a novel methodology of deep learning-enhanced Shapley value allocation (DESVA), which proposes to estimate Shapley values within deep neural networks (DNNs) in the context of healthcare staff allocation. Shapley values are a concept from cooperative game theory used to distribute the "credit" or contribution of each feature or player in a system fairly to an overall outcome. In healthcare, Shapley's values help determine the importance of individual healthcare staff members in contributing to effective staff allocation and workload management. The heart of our approach lies in understanding the intricate interplay between patient needs, staff capabilities, and the dynamic nature of healthcare environments (He et al., 2019; Macedo et al., 2019; Yu et al., 2015). By systematically assessing healthcare professionals' knowledge, skills, and expertise, our approach fosters cooperation among staff members, leading to a more balanced distribution of workloads. Furthermore, it considers the diverse teams operating within healthcare facilities, acknowledging that team dynamics and effectiveness vary.

The main motivation behind this research is to manage the workgroup's workload effectively. The staff in the hospital require a daily work plan; if it doesn't work, it leads to uneven work distribution. This creates inequality among the staff and results in improper resource management. This inefficiency directly impacts patient satisfaction and the timeliness of treatment. The proposed DESVA approach aims to revolutionise these traditional methods by introducing a sophisticated, data-driven model. A core goal of this research is to enhance patient experiences in healthcare facilities. By ensuring equitable and intelligent staff allocation, the DESVA approach minimises treatment delays and improves patient satisfaction, contributing to better healthcare outcomes.

Our study introduces a distinctive application of game-theoretic modelling within the healthcare sector and broadens its relevance beyond patient care. Professionals in software development and decision-makers in diverse fields can find valuable insights in our approach, enabling them to optimise resource allocation and attain optimal outcomes in their respective domains. Our proposed DESVA stands as a robust solution, promising to enhance staff resource allocation and minimise patient wait times, ultimately elevating the overall quality of healthcare services systematically and fairly. To validate these claims, we conduct simulation experiments in subsequent sections, providing concrete evidence of the effectiveness of our proposed DESVA.

The main contributions of the paper are as follows.

- We proposed a novel DESVA approach for effective staff allocation in the healthcare sector.
- The DESVA approach leverages the formidable capabilities of Shapley Values within Deep Neural Networks (DNNs) using cooperative game theory principles.

2 Literature review

2.1 Staff allocation and decision-making discussions

In response to the COVID-19 pandemic (Dunn et al., 2020), healthcare providers are adapting their staffing and care models, necessitating reallocating healthcare professionals to high-risk critical care settings. This paper delves into the ethical implications of staff allocation changes during the pandemic. It argues that healthcare professionals shouldn't be ethically obligated to treat patients when it puts them at risk. It highlights the need for a thoughtful process to shift staff from their usual roles due to changing healthcare needs. Resource allocation for preventive health interventions (Ananthapavan et al., 2022) in the NSW Government, Australia. It highlights a disconnect between the NSW Treasury, emphasising economic efficiency, and the NSW Ministry of Health, which mainly uses economic evidence for inter-agency persuasion. Barriers include capacity constraints, departmental collaboration gaps, and suboptimal inter-sectoral decision-making processes. The study advocates institutional changes to promote a comprehensive government-wide strategy and align with best practices in resource allocation.

The COVID-19 pandemic has underscored the importance of efficient medical resource allocation (Wang et al., 2022). While ethical frameworks exist, translating them into practical, legally compliant hospital protocols is complex. In Maryland, a consortium of five health systems representing a substantial portion of the state's hospitals collaborated to create resource allocation guidelines. These guidelines encompass diverse resources like ventilators, ICU capacity, blood products, and therapies, requiring customised algorithms due to their unique nature. Developing and refining these allocation processes is an ongoing endeavour, and the authors share their insights to aid other regions dealing with similar resource allocation dilemmas in times of public health crises.

The study (Kekkonen et al., 2018) explores the impact of rational task allocation between nursing staff and support service providers in healthcare, aiming to enhance work system outcomes. Using a work system model and integrating resilience and cost concepts, the study employs qualitative case studies and participatory design to optimise cooperation between personnel groups. The findings emphasise that rational support services should be comprehensive, resilient, reliable, and easily accessible to improve the healthcare environment.

District-level decision-making for maternal and child health resource allocation in India underscores the significance of data-sharing and inter-departmental coordination (Hu et al., 2022). The findings indicate deficiencies in structured decision-making processes and data-sharing, leading to the underutilisation of available data for planning. The study underscores the potential for enhanced collaboration and data-driven decision-making at the district level to improve health outcomes.

Creating an ethical (Guidolin et al., 2022) decision-making tool for COVID-19 resource allocation. The authors formed an interdisciplinary team to develop a stepwise, semiquantitative tool that integrates institutional objectives, procedural values, ethics, and decision criteria. This tool is designed to assist healthcare leaders in making fair and ethically sound resource allocation decisions during the pandemic and in the future.

Resource allocation decisions (Dawson et al., 2020) during the COVID-19 pandemic in New South Wales, Australia. A working party of ethicists and clinicians created the framework in a question-and-answer format, designed to be accessible and practical for decision-makers. This framework underwent multiple revisions based on feedback from experts and the public before being made available online within a short timeframe, aiming to provide a valuable resource for addressing resource constraints during pandemics.

Sustainability in Health Care by Allocating Resources Effectively (SHARE) program (Maritta et al., , 2021) aimed to address disinvestment in an extensive Australian health service network systematically. The program, conducted in three phases, sought to identify and implement disinvestment opportunities within the organisational infrastructure, integrate disinvestment with all resource allocation decisions, consider non-monetary resources, and optimise healthcare outcomes with limited resources. This approach contributes to understanding systematic disinvestment in local healthcare and has policy, practice, and research implications.

Here (Harris et al., 2017), the SHARE program focuses explicitly on developing, implementing, and evaluating support services within a large Australian health service. These services aimed to facilitate evidence-based decision-making for resource allocation, including disinvestment, and required expertise, education, training, and support for health service staff. The methods used included literature reviews, surveys, interviews, consultation, workshops, and applying theoretical frameworks to evaluate processes and outcomes.

The discussion (Chaovalitwongse et al., 2017) focuses on the Princess Mother's Medical Volunteer (PMMV) Foundation in Thailand, which provides free mobile medical services in remote areas with limited access to healthcare. The paper proposes a decision support model in the form of a computer information system (CIS) to optimise the allocation of volunteer medical staff (Nikkhoo et al., 2023) to operation sites. This model aims to streamline data organisation, improve efficiency, and minimise transportation costs (Ghadermazi & Chan, 2023). The research outcomes were positive, indicating its effectiveness in enhancing the allocation process (Ashraf et al., 2023).

There are more studies discussed on decision support systems. However, decision-making accuracy becomes a major issue. Sometimes, simple errors in decision-making result in improper staff management. This leads to work incompleteness and some work over-completion. The proposed model based on the game theory approach has addressed this research gap.

3 Methodology

3.1 System overview

The DESVA system model for healthcare staff allocation comprises several interconnected components that work collaboratively to optimise the allocation of healthcare personnel. At its core are DNNs, which serve as the modelling backbone. These DNNs are trained using pre-processed healthcare data, including patient needs, staff qualifications, historical allocation patterns, and performance metrics. The DNNs are tasked with capturing the intricate relationships between these data elements to make allocation recommendations. The unique feature of DESVA lies in its application of Shapley values, calculated using a customised Deep Shapley Algorithm. These Shapley values quantify the contributions of individual staff members to the staff allocation process, enabling a fair and efficient allocation strategy. The Shapley values are seamlessly integrated into the staff allocation algorithm, ensuring tasks are assigned based on each member's unique strengths and capabilities. The system generates comprehensive outputs, including staff allocation decisions and Shapley values, which are valuable insights for healthcare administrators. Optionally, a feedback loop can be incorporated for continuous improvement, allowing DESVA to adapt and enhance staff allocation efficiency over time. Overall, the DESVA system model combines the strength of deep learning, Shapley value calculations, and real-time allocation to revolutionise staff allocation in healthcare, ultimately improving patient care quality and operational efficiency.

3.2 Proposed DESVA architecture

As per the study discussed under (Ancona et al., 2019), we adopt the deep approximate Shapley Propagation (DASP) technique to allocate staff effectively in the healthcare sector. How is it possible to explain the below considerations? The DASP works in the context of DESVA are described as follows.

3.2.1 DNN

DNNs are at the heart of DESVA and play a crucial role. They are deep-learning models designed to capture complex relationships within healthcare data. In staff allocation, DNNs are trained on healthcare-specific data, such as patient needs, staff qualifications, historical allocation patterns, and performance metrics. These networks learn how various factors relate to each other and, ultimately, impact staff allocation.

3.2.2 Co-operative game theory (Shapley Values) quantifying contributions

Shapley values, a concept from cooperative game theory, are used to quantify the contributions of individual staff members in the staff allocation process. They offer a way to fairly assess and distribute each staff member's value in allocating healthcare resources (Ancona et al., 2019).

3.2.3 DASP

DASP addresses the computational challenges associated with calculating Shapley values, particularly in the context of complex DNNs like those used in DESVA. This approximation technique is vital for maintaining computational efficiency. DASP employs a perturbation-based approach, which means it doesn't attempt to compute Shapley values in their exact, often computationally expensive form. Instead, it perturbs the input data during the calculation process. Here's how it works: DASP systematically removes the contribution of a single staff member from the input data, simulating the absence of that member's impact on staff allocation. It then assesses the resulting allocation outcome. This procedure is repeated for various coalitions of staff members, each time evaluating how the absence of a particular member influences the allocation. These impact assessments are then aggregated to approximate the Shapley values. One of the strengths of DASP is its seamless integration with DNNs. Deep learning models like DNNs are exceptional at processing and comprehending complex healthcare data. DASP takes advantage of this capability by calculating Shapley values concurrently with the DNN's data processing. This integration is smooth and natural within the DESVA framework, as it ensures that staff allocation decisions are made in real-time or during model training, incorporating fairness and equity considerations into the allocation process. DASP becomes an integral part of DESVA's decision-making process, contributing to the system's effectiveness in healthcare staff allocation.

3.2.4 Performance of DESVA in efficient staff allocation

The combined power of DNNs and DASP equips DESVA with the capability to allocate healthcare staff resources efficiently. DNNs excel at capturing the intricate details and complexities of the healthcare environment, providing the system with a deep understanding of the context in which staff allocation decisions are made. On the other hand, DASP ensures that these decisions are fair and just, as it calculates Shapley values to compensate staff members fairly for their contributions. Integrating Shapley values, determined by DASP, into the DESVA framework is pivotal in making the system's equitable and well-informed resource allocation decisions. Staff members are assigned tasks and responsibilities based on their contributions, ensuring that resources are utilised efficiently and that staff members are recognised for their input. DESVA can be designed with a feedback loop to enhance its effectiveness further. This feedback mechanism allows the system to improve its staff allocation strategies continuously. Real-world outcomes or simulation results can be fed into the system, enabling it to adapt and respond to changing healthcare needs. In this way, DESVA evolves, becoming more refined and better equipped to meet the dynamic demands of the healthcare industry.

3.3 Deep Shapley Algorithm to calculate the Shapley values of staff

Input: Healthcare data x, coalition sizes k_1, ..., k_k, initial weights for staff capabilities w, customized DNN model F_c

Step 1: Initialize result vector R^c for Shapley values at zero
Step 2: for each staff member $i = 1 to N$ do
Step 3: for each coalition size $k = k_1, ..., k_k$ do
Step 4: Perturb the data to compute Shapley values
Step 5: $\overline{x} = x$
Step 6: $\overline{x}[i] = 0$
Step 7: Compute statistics of features excluding i
Step 8: $\mu = \frac{1}{n-1}(W\overline{x})$ // where W represents network weights
Step 9: Compute variance
Step 10: $\sigma^2 = \frac{1}{n-1}\left(W^2\overline{x}^2\right) - \mu^2$
Step 11: Compensate for the current coalition size
Step 12: $\mu = k\mu$
Step 13: $\sigma^2 = k\frac{k-1}{n-1}\sigma^2$
Step 14: Compute bias introduced by i
Step 15: $\overline{\mu} = \mu + x[i]w^{(1)}$
Step 16: Propagate distributions up to the output layer
Step 17: $\mu^{(l)}, \sigma^{2^{(l)}} = \hat{F}_c\left(\mu, \sigma^2\right)$
Step 18: $\overline{\mu}^{(l)}, \overline{\sigma}^{2^{(l)}} = \hat{F}_c\left(\overline{\mu}, \sigma^2\right)$
Step 19: Compute marginal contribution of i to coalitions of size k
Step 20: $R^c[i] = R^c[i] + \frac{1}{k}\left(\overline{\mu}^{(l)} - \overline{\mu}^{(l)}\right)$
Step 21: end for
Step 22: end for
Step 23: Output: Approximate Shapley values R^c

The algorithm begins by initializing a result vector R^c, which will store the Shapley values for each staff member within coalition c. This vector is initialized with zeros. Then, it enters two nested loops, the first one iterating over each staff member (indexed by i), and the second one looping through different coalition sizes (indexed by k). Within these loops, the algorithm perturbs the data to calculate Shapley values. It creates a perturbed dataset $\overline{x}$ by setting the data of the current staff member i to 0 while keeping other data unchanged. Statistics are then computed on this perturbed dataset to estimate Shapley values, including the mean μ and variance σ^2. Afterwards, the algorithm compensates for the current coalition size k by adjusting the mean and variance based on the coalition size. The mean μ is multiplied by k, and the variance σ^2 is adjusted accordingly. The bias introduced by staff member i is calculated, and the mean is updated to $\overline{\mu}$ by adding the bias term $\overline{\mu} = \mu + x[i]w^{(1)}$. Next, the algorithm propagates these distributions through a customized DNN model F_c up to the output layer. This involves computing new means and variances at each layer of the neural network. Once the distributions are propagated, the algorithm calculates the marginal contribution of staff member i to coalitions of size k, which is used to update the Shapley value for staff member i in coalition c. These steps are repeated for each staff member and each coalition size. Finally, the algorithm outputs the approximate Shapley values R^c, which contain the Shapley values for each staff member within coalition c. In essence, it iteratively

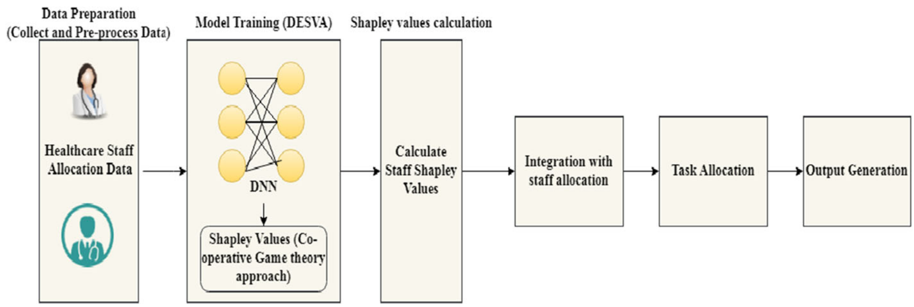

Fig. 1 Proposed DESVA Architecture

perturbs the data, accounts for coalition size and bias, and uses a DNN model to estimate Shapley values for staff members in the healthcare data context.

4 Results and experiments

4.1 Experimental setup

In this study, the proposed DESVA's performance in healthcare staff allocation is evaluated using data from the Statistical Yearbook of Sichuan Province and the Health Yearbook of Sichuan Province, covering the years 2010–2018. To gain a comprehensive understanding of the dataset's structure, readers are directed to a previous study for a more detailed explanation (Gong et al., 2023). The primary objective is to assess the effectiveness of DESVA in healthcare staff allocation, and to achieve this, DESVA's performance is compared against well-established techniques and models. These models include Deep Belief Network (DBN), Restricted Boltzmann Machine (RBM), Convolutional Neural Network with Gated Recurrent Unit (CNN-GRU), Long Term Short Term Memory (CNN-LSTM), and Generated Adversarial Network based on Recurrent Neural Network (GAN-RNN) (Harrou et al., 2022). This comparative analysis aims to highlight the strengths and weaknesses of DESVA and determine its suitability for enhancing healthcare staff allocation practices (Fig. 1).

4.2 Evaluation metrics

In our evaluation of the proposed DESVA, we employ widely used metrics to assess its performance. These metrics include accuracy, precision, recall, and F1-Score. To comprehensively evaluate DESVA, we conduct experiments using data from the province from 2010 to 2012, 2013 to 2015, and 2016 to 2018. These periods serve as distinct test cases, allowing us to analyse how well DESVA performs in various scenarios and providing insights into its effectiveness and robustness over time.

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + TN + FP} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$
\mathrm{F1} = \frac{2 * Precision \times Recall}{Precision + Recall} \tag{4}
$$

Figure 2 presents the performance evaluation in terms of accuracy of various models DBN, RBF, CNN-LSTM, CNN-GRU, GAN-RNN and DESVA across different time periods revealed distinct trends. From 2010 to 2012, the models exhibited varying accuracy levels, with the Proposed DESVA standing out with an impressive accuracy of 98%, accompanied by high precision and recall values. In the subsequent period of 2013–2015, all models showed improvement, but the Proposed DESVA maintained its superiority with an accuracy of 97.5%, and this trend continued from 2015 to 2018. Despite some fluctuations, the Proposed DESVA consistently excelled with an exceptional accuracy of 98%, affirming its reliability and robustness in healthcare staff allocation throughout all time periods.

The Proposed DESVA demonstrates remarkable and consistent precision efficiency across different time periods when compared with different models of DBN, RBM, CNN-LSTM, CNN-GRU, GAN-RNN which is illustrated in Fig. 3. Precision, a pivotal metric for assessing a model's accurate positive predictions, underscores how effectively the Proposed DESVA assigns healthcare staff responsibilities based on their contributions. During 2010 to 2012, the model's precision consistently ranged from 95 to 96.24%. This signifies its ability to identify and allocate staff members with remarkable accuracy, yielding minimal false positives. Subsequently, from 2013 to 2015, precision improved further, consistently ranging from 95.6 to 96.89%, reinforcing the model's proficiency in precise staff allocation. The period spanning 2016–2018 saw sustained high precision, ranging from 97 to 98%. This reaffirms the model's unwavering competence in accurately assigning tasks to staff members based on their contributions

The effectiveness of the Proposed DESVA in terms of recall, as depicted in Fig. 4, showcases its consistent and superior performance in correctly identifying relevant instances, particularly in the healthcare staff allocation context. Recall measures a model's ability to capture and correctly identify all relevant instances out of the total true positive cases. In

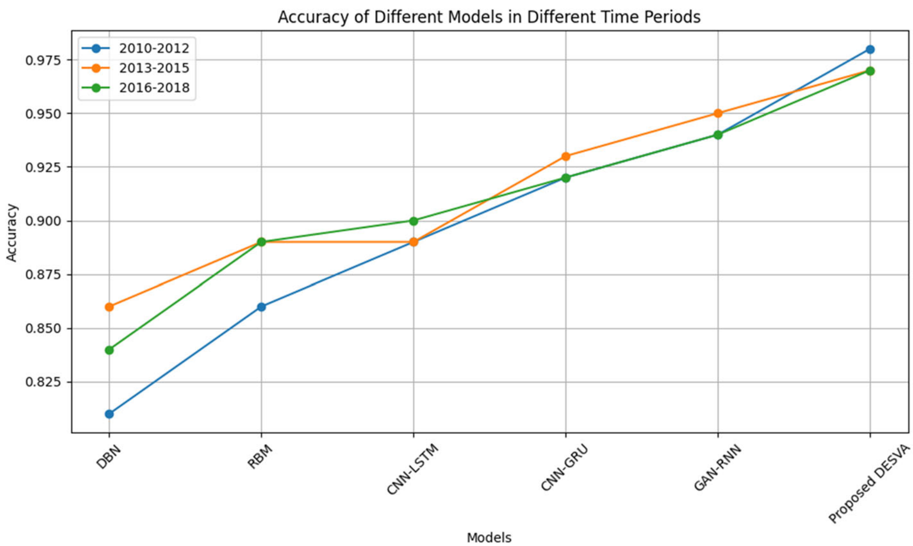

Fig. 2 Accuracy comparison with existing models

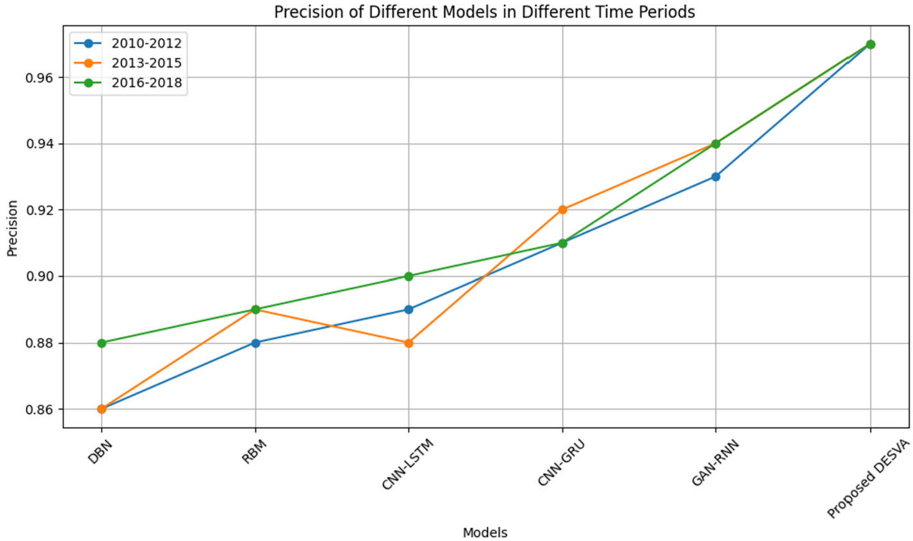

Fig. 3 Precision percentage of different models

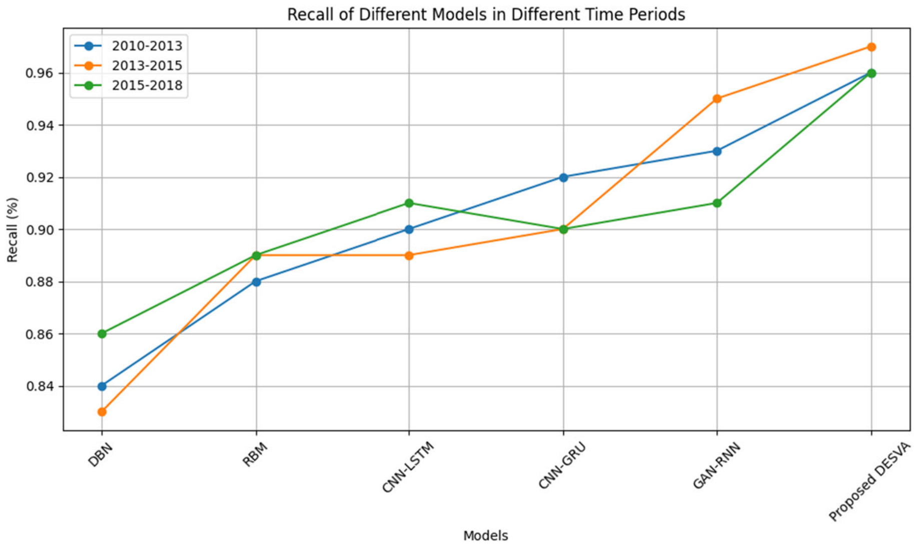

Fig. 4 Recall comparison

this evaluation, the Proposed DESVA consistently outperforms other models over different time periods, including DBN, RBM, CNN-LSTM, CNN-GRU, and CNN-RNN. From 2010 to 2012, the Proposed DESVA exhibited recall values ranging from 96.15 to 97.27%, indicating its proficiency in identifying and allocating healthcare staff accurately. This is vital in ensuring that no critical tasks or responsibilities are overlooked. Throughout 2013–2015, the Proposed DESVA maintained its superior recall, with values ranging from 97.12 to 98.04%.

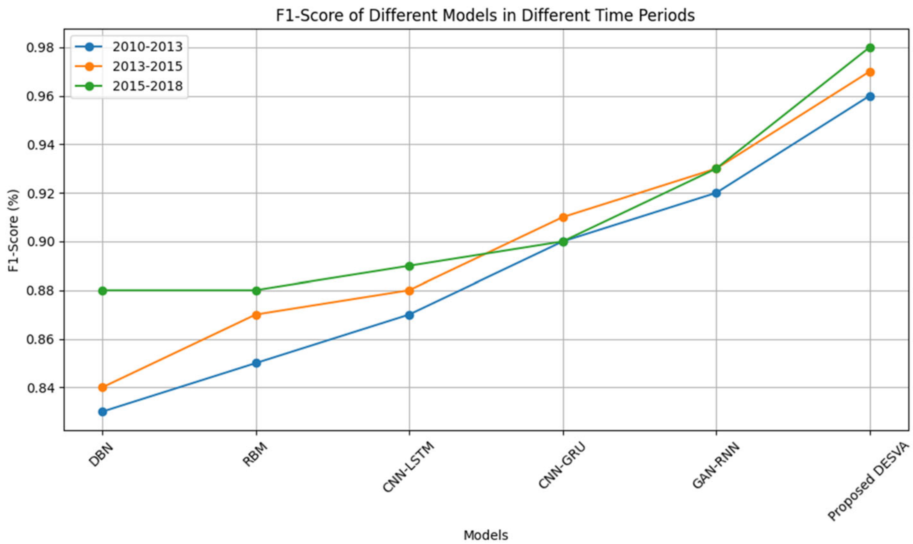

Fig. 5 F1-Score

This highlights its reliability in consistently recognizing relevant instances, even as the dataset evolves. From 2016 to 2018, the model sustained its exceptional recall performance, ranging from 96.57 to 98.12%. This reaffirms its ability to capture and allocate staff members to tasks effectively, reflecting its reliability and effectiveness in healthcare staff allocation.

The efficiencies of the Proposed DESVA, as illustrated in Fig. 5, are strikingly evident and demonstrate its consistent and superior performance compared to other models, as indicated by the F1-score—a comprehensive metric that combines both precision and recall. From 2010 to 2012, the Proposed DESVA displayed impressive F1-scores ranging from 95.42 to 96%. This signifies its remarkable ability to maintain a balance between making precise positive predictions and ensuring that no relevant instances are overlooked. In healthcare staff allocation, this equilibrium is vital to guarantee both the accuracy of task assignments and comprehensive coverage. During the years 2013 to 2015, the Proposed DESVA sustained its exceptional F1-score performance, ranging from 96.45 to 97.38%. This underscores its continued effectiveness in making precise staff allocation decisions while minimizing the likelihood of missing relevant instances. From 2016 to 2018, the model consistently achieved outstanding F1-scores, ranging from 97.14 to 98%. These remarkable values reaffirm the model's proficiency in healthcare staff allocation, highlighting its reliability and efficacy across diverse scenarios and evolving datasets.

The efficiency of the Proposed DESVA becomes evident when examining the overall performance values depicted in Figure 6, which represent accuracy scores achieved by different models across various time periods. Starting with the period from 2010 to 2012, the Proposed DESVA stands out with an accuracy score of 96.24%. This signifies its ability to make highly accurate staff allocation decisions during this time frame, surpassing other models. Moving into the years 2013 to 2015, the Proposed DESVA maintains its impressive accuracy performance at 97.16%. This demonstrates its consistent ability to assign healthcare staff members with precision and accuracy. From 2016 to 2018, the Proposed DESVA continues to excel, achieving an accuracy score of 98.20%. This signifies its reliability in consistently

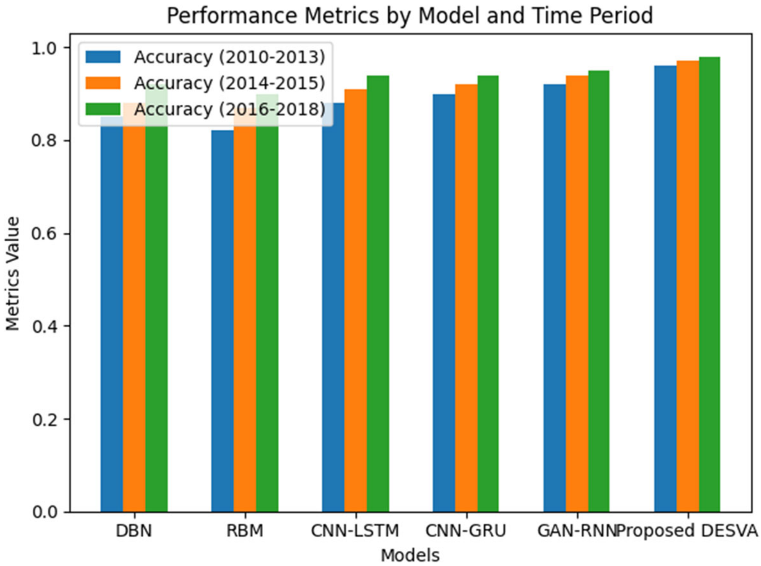

Fig. 6 Overall performance comparison

making accurate staff allocation decisions, contributing to effective resource optimization in healthcare settings.

Integrating feedback mechanisms into the DESVA approach is not just a tool for improvement; it's a strategic move towards creating a more adaptable, user-friendly, and patient-centric system. This approach underscores the importance of evolving healthcare management practices to meet the real-world demands of both healthcare providers and patients.

5 Conclusion

In conclusion, this paper presents a novel and efficient approach, known as DESVA (Deep Learning-Enhanced Shapley Value Allocation), for optimizing staff allocation within the healthcare sector. Leveraging the cooperative game theory concept of Shapley values within Deep Neural Networks (DNNs), DESVA offers a promising solution to the complex task of resource allocation in healthcare settings. Our evaluation is based on extensive data from the Statistical Yearbook of Sichuan Province and the Health Yearbook of Sichuan Province, encompassing the years 2010 to 2018. By comparing DESVA with established models such as DBN, RBM, CNN-LSTM, CNN-GRU, and GAN-RNN, we have demonstrated its efficacy in healthcare staff allocation. Our experiments, conducted separately for the time periods of 2010–2012, 2013–2015, and 2016–2018, reveal that DESVA consistently outperforms these models, reaffirming its robustness and adaptability across different scenarios. As we look to the future, we anticipate further enhancements in our approach through the integration of updated models and techniques. The results obtained thus far underscore the potential of DESVA as a valuable tool for healthcare institutions seeking to optimize resource allocation, minimize patient wait times, and ultimately improve the quality of healthcare services in a structured and equitable manner. The path forward involves continued refinement and adaptation to meet the evolving needs of the healthcare sector.

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Declarations

Conflict of interests The authors declare that they have no competing interests.

Ethics approval and consent to participate Not applicable

Consent for publication Not applicable

Humal or Animal participants (In case animals were involved) This article does not contain any studies with human participants or animals performed by any of the authors.

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