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Integrated LSTM and PCNN Framework for Heart Disease Prediction, Treatment Recommendation, and Side Effects Management

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Abstract: Heart disease remains a predominant cause of mortality globally, necessitating advanced predictive, prescriptive, and management strategies to enhance patient outcomes. This paper presents a comprehensive framework utilizing machine learning and data mining techniques for heart disease prediction, treatment recommendation, and side effects management. Firstly, we employ Long Short-Term Memory (LSTM) to expect heart disease by analyzing temporal dependencies in patient health records, achieving high accuracy through effective handling of time-series data. Secondly, we introduce a Pulse Coupled Neural Network (PCNN)-based treatment recommendation system that identifies optimal treatments by recognizing complex patterns in patient data and synchronizing neuron responses to deliver personalized therapy suggestions. Thirdly, we address side effects management by implementing standardized treatment protocols derived from extensive data mining of clinical records, which helps in mitigating adverse effects and refining therapeutic approaches. The integration of these components into a unified data mining application demonstrates significant potential in transforming heart disease care, providing a robust tool for clinicians to make informed decisions, improve patient care, and streamline healthcare processes.

Keywords: *Clinical Records, Data Mining. Heart Disease, Long short term memory, Pulse coupled neural network, treatment Protocol.*

1. Introduction

According to data provided by the World Health Organisation (WHO), cardiovascular disease continues to be one of the major causes of death around the globe, as it is responsible for roughly 17.9 million deaths each year. Because of the complexity and variety of cardiovascular disorders, sophisticated techniques are required for early prognosis, successful treatment, and thorough management of the risks and side effects associated with these illnesses. The creation of predictive models, personalised treatment recommendations, and standardised procedures for the control of side effects are all made possible by recent advancements in data mining and machine learning (ML), which provide tremendous promise in solving these difficulties.A solid basis for predictive analytics is provided by the proliferation of big data in the healthcare industry, which includes electronic health records (EHRs), medical imaging, genetic data, and real-time patient monitoring systems [1].

The LSTM networks, which are a sort of recurrent neural network (RNN), have shown remarkable potential in modelling temporal sequences and dependencies. This is among the many machine learning approaches that have been developed. Because of their capacity to deal with long-term dependencies in patient data, LSTM networks are especially well-suited for the prediction of heart disease. This ability is essential for accurately recording the evolution of cardiovascular problems over the course of time.The traditional techniques of diagnosing cardiac disease and planning therapy have depended mainly on statistical analysis and clinical judgement. This has often resulted in suggestions that are more general in nature and may not be tailored to the specific requirements of each particular patient concerned. A change towards precision medicine is made possible by the combination of data mining and machine learning. This shift enables predictive models to evaluate the probability of cardiac disease on a per-patient basis, taking into account parameters [2].

This personalized approach not only enhances the accuracy of predictions but also informs tailored treatment plans that align with the unique profiles of patients. In addition to prediction, effective management of heart disease involves recommending appropriate treatments and monitoring their outcomes. The treatment landscape for cardiovascular conditions is diverse, ranging from lifestyle modifications and pharmacotherapy to invasive procedures like angioplasty and bypass surgery. An intelligent treatment recommendation system can assist healthcare providers by suggesting the most suitable interventions based on predictive analytics and evidence-based guidelines. Such systems employ algorithms like collaborative filtering and content-based filtering to match patient profiles with optimal treatment plans, thereby improving clinical decision-making and patient adherence [3].

Managing the side effects of treatments is another critical

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component of heart disease care. Adverse drug reactions (ADRs) and complications from medical procedures can significantly impact patient outcomes and quality of life. Data mining techniques can be leveraged to analyze large datasets of clinical trials, EHRs, and patient feedback to identify patterns and correlations in side effects occurrence. This information can be used to develop standardized treatment protocols that mitigate risks and manage side effects effectively. Implementing a feedback loop where patient experiences are continuously monitored and incorporated into the system helps refine treatment recommendations and enhances the overall care process. The development of comprehensive data mining applications in healthcare requires a multidisciplinary approach, combining expertise in medicine, computer science, and bioinformatics [4].

System architecture for such applications typically involves a robust infrastructure capable of handling vast amounts of heterogeneous data, advanced analytics platforms for model training and validation, and user-friendly interfaces for clinicians and patients. Real-world implementation of these systems poses challenges. Despite these challenges, the potential benefits of integrating data mining and machine learning in heart disease management are substantial. Improved prediction accuracy can lead to earlier interventions, reducing the incidence of severe cardiovascular events. Personalized treatment recommendations can enhance the effectiveness of therapies, reduce trial-and-error in medication prescription, and increase patient satisfaction. Effective management of side effects can prevent complications, minimize hospital readmissions, and improve long-term health outcomes [5].

The proposed work contributions:

i. The authors begin by discussing datasets, which are then standardised and improved upon in the following steps. After that, these datasets are used to train and test a number of different classifiers in order to identify the one that has the greatest level of accuracy.

In the next step, the authors make use of the correlation matrix in order to categorise the most advantageous values or characteristics.

ii. The third phase entails applying the classifiers to the dataset that has been pre-processed, with the goal of achieving the best possible accuracy via the change of the parameters.

This research paper is broken down into many pieces, which are provided as follows: Literature review is the topic of discussion in Section II. Section III provides a comprehensive explanation of the methodology and approach taking place. The results of the experiment and the analysis are described in further depth in Section IV. In conclusion, Section V comes to a close.

2. Related Work

A number of researchers have carried out studies with the purpose of predicting the prevalence of cardiovascular disease by making use of electronic health records (EHR) or regular clinical data obtained from primary health care institutions or family businesses. EHRs have been used either on their own or in combination with a variety of machine learning techniques in order to make predictions about coronary heart disease (CHD). For the purpose of predicting cardiac problems, it has been shown that algorithms for machine learning provide useful solutions.

With the use of an artificial intelligence-supervised reinforcement learning (SRL) LSTM, Haihong et al. created a treatment technique that was framed as a sequential decision-making issue. The experiments were carried out utilising a real-world database. A random forest technique was used. This was done in order to improve the interpretability of the AI model [6]. A New Feature Reduction (NFR) model was suggested by Syed and colleagues with the intention of enhancing performance by lowering error rates and aligning with ML and data mining methods. In the first technique, the optimum subset of characteristics that contribute the most to the accuracy of the prediction and the area under the curve (AUC) is determined. In the second technique, individual feature accuracies and AUCs are evaluated in order to identify subsets that have the greatest performance metrics. A feature reduction of 41.67% was achieved by this model when it was evaluated using public cardiac datasets from the UCI ML repository. This is a 4.22% gain in accuracy and a 25% increase in algorithm performance when compared to experiments that have already been conducted [7].

In order to provide an accurate forecast of heart illness, Pronab et al. presented a model that combines a number of different methodologies. The development of a trustworthy training dataset was made possible by using efficient methods of data collection, preprocessing, and transformation. They constructed hybrid classifiers by combining classic classifiers with bagging and boosting approaches. They then presented each set of findings in their own unique way [8]. It was recommended by Jianguo and colleagues that the Density-Peaked Clustering Analysis (DPCA) approach be used for the purpose of disease-symptom clustering that is more accurate. This strategy directs patients and inexperienced clinicians towards suitable diagnostic and treatment options, especially in therapeutic situations with limited resources. Additionally, in order to provide high-speed answers with minimal latency, they created a parallel DDTRS solution on the Apache Spark cloud platform. According to the results of the experiments, the DDTRS that was presented is capable of efficiently clustering illness symptoms and producing relevant therapy recommendations [9]. New procedures for predicting cardiovascular disease (CVD) based on patient symptoms and other information from hospital records were suggested by Nadiah and colleagues. For the purpose of heart disease categorization and prediction, their system performed better than other algorithms that were already in existence in terms of accuracy and precision. In order to establish a system that is more accurate and robust for the early diagnosis and prognosis of cardiac illnesses [10].

In this paper propose a comprehensive technique for improving heart disease management using advanced AI techniques. First, use LSTM networks to predict heart disease by analyzing time-series data from patient health records, which helps in identifying potential cases early. Next, implement a PCNN based system to recommend personalized treatments by recognizing complex patterns in patient data. Additionally, manage side effects by developing standardized treatment protocols based on extensive data mining of clinical records. This integrated approach aims to assist clinicians in making informed decisions, enhance patient care, and streamline healthcare processes.

3. Methodology

In this study, propose a comprehensive approach for the management of heart disease, encompassing predictive modeling, treatment recommendation, and side effects management, leveraging the capabilities of data mining and machine learning techniques. The proposed method consists of three main components: heart disease prediction using LSTM networks, treatment recommendation using PCNNs, and side effects management with standardized treatment protocols. Each component addresses specific challenges in heart disease care, aiming to improve early detection, personalized treatment, and patient outcomes.

The first component of the proposed method focuses on predicting heart disease using LSTM networks. In this context, The LSTM architecture consists of multiple layers of LSTM units, which process sequential patient data and learn to identify patterns indicative of heart disease risk. During training, the model learns to capture complex temporal dynamics, enabling it to make accurate predictions based on sequential input data. The second component of the proposed method focuses on treatment recommendation using PCNNs. PCNNs are capable of detecting patterns and synchronizing responses based on input stimuli, making them suitable for personalized treatment recommendation in heart disease management. In this component, PCNN models are trained on a comprehensive dataset of patient records, treatments, and outcomes to learn the associations between patient characteristics and treatment responses. PCNN architecture consists of interconnected neurons that communicate through pulses, with each neuron representing a specific treatment option. During training, the PCNN model learns to synchronize neuron responses based on patient data, generating recommendations for the most suitable treatment based on learned patterns. The third component of the proposed method focuses on side effects management with standardized treatment protocols. Adverse drug reactions and treatment complications are common in heart disease management and can significantly impact patient outcomes. To address this challenge, we employ data mining techniques to analyze large datasets of clinical trials, EHRs, and patient feedback to identify patterns and correlations in side effects occurrence. Based on the insights gained from data mining, standardized treatment protocols are developed to mitigate risks and manage side effects effectively. These protocols provide guidelines for healthcare providers on the prevention, monitoring, and management of side effects associated with specific treatments. Continuous monitoring of patient experiences and feedback allows for refinement of the treatment protocols, ensuring that they remain up-to-date and aligned with best practices in heart disease management. The Fig.1 illustrates a comprehensive method for heart disease management, integrating data preprocessing, disease prediction, treatment recommendation, and side effect detection. Initially, patient data from the database undergoes normalization, scaling, and cascading during the pre-processing stage to ensure consistency and quality. This processed data is then fed into an LSTM model to predict heart disease. If the LSTM model predicts heart disease, the system proceeds to the treatment recommendation phase, where a severity detection module assesses the patient's condition based on a predefined threshold. A trained PCNN then provides personalized treatment recommendations. Concurrently, the side effect detection module utilizes a medicine and side effects database to identify potential adverse effects of the recommended treatments. This integrated approach aims to support clinicians in making informed decisions, improving patient care by predicting disease, recommending treatments, and managing side effects effectively.

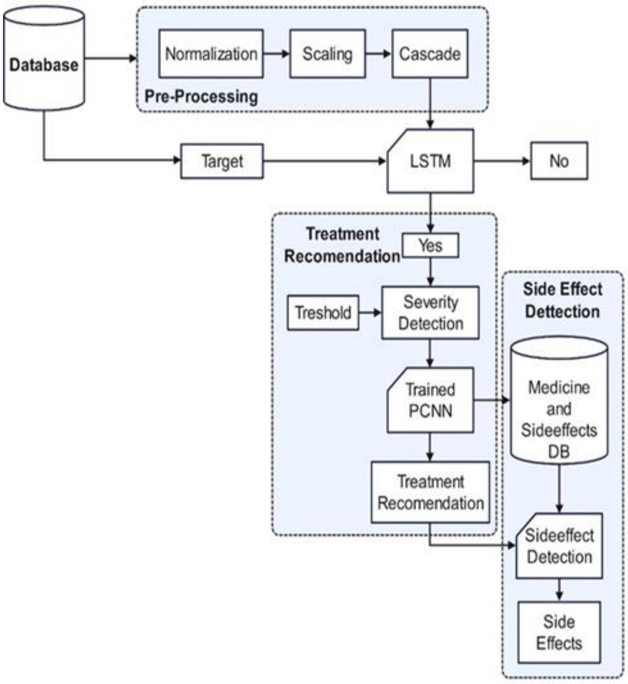

Fig.1. Block diagram of proposed method

3.1. Data Normalization

Normalization is a critical preprocessing step in preparing data for machine learning models, especially for deep learning architectures like LSTM networks. It involves scaling the data so that each feature contributes equally to the learning process, which helps in speeding up the convergence of the gradient descent algorithm and improving model performance []11. This section will cover why normalization is important, the different techniques for normalization, and how to implement it for heart disease prediction. Min-Max Scaling technique scales the data to a fixed range, usually [0, 1]. It transforms each feature individually according to the formula:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

where $\boldsymbol{X}$ is the original value, X_{min} and X_{max} are the minimum and maximum values of the feature, and X' is the normalized value.

3.2. LSTM

Traditional recurrent neural networks (RNNs) have a number of limitations that need to be addressed. One of these limitations is the vanishing gradient issue that renders it hard for RNNs to acquire dependency over time. The LSTM networks are a specialized version of RNNs that try to solve these problems. In the context of heart disease prediction, LSTM networks are highly effective due to their ability to retain and utilize information from long sequences of patient data over time. This makes LSTMs ideal for analyzing time-series data such as EHRs which often include periodic health measurements and patient history. An LSTM network is composed of a series of units, each containing a memory cell and three types of gates: the forget, the input, and the output gate [12-14]. These gates allowing the network to maintain long-term dependencies without suffering from the issues that plague standard RNNs [15-17]. Fig.2.shows the structure of LSTM.

The operation of an LSTM unit can be mathematically described by the following set of equations: Forget Gate decides which information should be discarded from the cell state.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \qquad (2)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \qquad (3)$$

The candidate values layer:

$$C_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \qquad (4)$$

The input gate's output is represented by i_t and C_t signifies the candidate values for updating the cell state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \qquad (5)$$

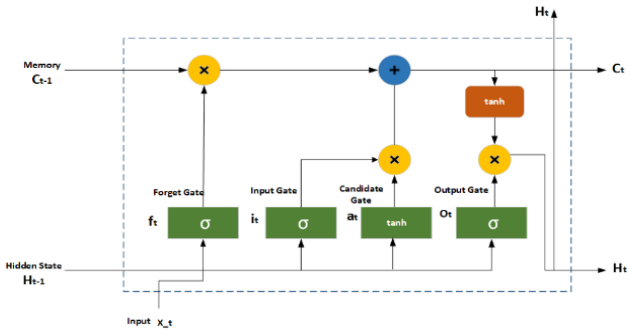

Fig.2.Structure of LSTM

Table 1. Shows the parameter Specification of LSTM. The LSTM model designed for heart disease prediction is specified with the following parameters. It consists of two LSTM layers, each containing 50 units. The model incorporates a dropout rate of 0.2 to prevent overfitting, and the activation function for the LSTM units is set to tanh, while the recurrent activation function is sigmoid. The model is optimized using the Adam optimizer with a learning rate of 0.01.

Table.1. Parameter specification of LSTM

Parameter	Value
Number of LSTM Layers	2
Units per Layer	50
Dropout Rate	0.2
Activation Function	tanh
Recurrent Activation	sigmoid
Optimizer	Adam
Batch Size	32

Epochs	50
Learning Rate	0.01

3.3. Pulse Coupled Neural Network

The PCNN are particularly effective for image processing tasks, but can also be adapted for use in healthcare for treatment recommendation systems by leveraging their ability to detect patterns and synchronize responses based on input stimuli. This section will describe how PCNNs can be utilized for recommending treatments for heart disease, focusing on their architecture, functioning, and the integration with patient data [18-19]. A PCNN consists of a network of neurons that are interconnected and communicate through pulses. Each neuron in a PCNN model consists of three main components:

Input Modulation processes the external input signal, which in the context of heart disease treatment recommendation, could be patient-specific data such as medical history, current symptoms, and clinical test results. Pulse Generation is based on the input modulation, neurons generate pulses. The generation of a pulse is influenced by the neuron's internal state and the stimuli received from neighboring neurons. Threshold Modulation dynamically adjusts the neuron's threshold based on its activity, allowing the neuron to become more or less sensitive to input over time.

The functioning of a PCNN can be mathematically described by the following equations:

$$F_{ij}[n] = I_{ij} + S_{ij}[n-1] + \alpha_F \cdot F_{ij}[n-1] \quad (6)$$

where $F_{ij}[n]$ is the feeding input of the neuron at position (i,j) at time step n, I_{ij} is the external input, $S_{ij}[n-1]$ is the sum of the linked inputs from neighboring neurons at the previous time step, and α_F is a decay factor. Fig.3. shows the structure of PCNN. Fig.3. shows the Structure of PCNN.

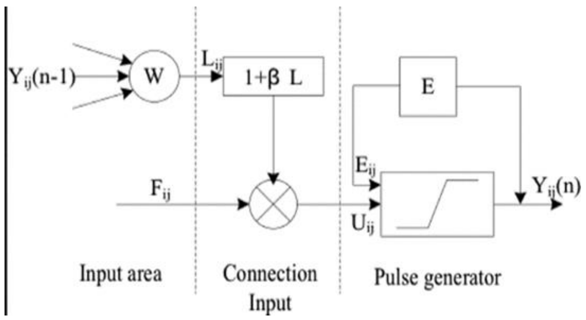

Fig.3. Structure of PCNN

4. Results and Discussions

A computer with a Pentium(R) Dual-Core CPU E5800 operating at 3.20GHz, 3192MHz, 2 Core(s), and 4GB of RAM is used to implement the suggested approach. Python Colab is used to develop the method.

4.1. Dataset

When using machine learning approaches to get precise outcomes, data is regarded as the first and most fundamental component. The applicable dataset was obtained from the "UCI machine learning repository," a reputable data source. The Hungary, Cleveland, Switzerland, VA Long Beach, and Statlog heart disease datasets are the five distinct datasets. In this study, we have integrated them all to get more precise results. From their database, more than 1190 examples and 14 unique traits are gathered into a text file [20]. These combined datasets thirteen properties are used as diagnostic inputs, and one attribute—the "num" attribute—is chosen as the output. They characteristics are deemed important in medical literature

Attributes: Description and Range Value

- Age: Age in years, ranging from 29 to 79.

- Chol: A range of 126 to 564 milligrams per deciliter for serum cholesterol.

- Sex: Gender instance, values 0 and 1.

- CP: Chest pain type, values 1, 2, 3, and 4.

- Thalach: The highest possible heart rate, which may range anywhere from 71 to 202.

- Trestbps: Blood pressure at rest measured in millimeters of mercury, from 94 to 200.

- FBS: Fasting blood sugar > 120 mg/dl, values 0 and 1.

- Restecg: Resting ECG results, values 0, 1, and 2.

- Num: Diagnosis of heart disease, values 0, 1, 2, 3, and 4.

- CA: Fluoroscopy may be used to determine the number of main vessels, which can range from 0 to 3.

- Exang: Activity-induced angina, with values ranging from 0 to 1.

- Oldpeak: When compared to rest, the ST depression that is generated by activity might range anywhere from one to three.

- Slope: Values 1, 2, and 3 regarding the slope of the peak workout ST section.

- Thal: Defect types, values 3

4.2. Performance Evaluation

Evaluating the performance of predictive models, treatment recommendation systems, and side effects management protocols in the context of heart disease involves a variety of metrics. These metrics provide a comprehensive understanding of the system's accuracy, effectiveness, and overall impact on patient outcomes. Below are the key performance metrics that are pertinent to each component of the proposed framework:

- Accuracy: The proportion of cases that were accurately predicted to all occurrences. It provides an overall indicator of how often heart illness is successfully predicted by the model [21]

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

- Precision: The proportion of accurate positive forecasts to the total of accurate positive and erroneous positive forecasts. Precision measures how well the model predicts favorable outcomes. [22].

$$Precision = \frac{TP}{TP + FP} \quad (8)$$

- Recall: The percentage of correctly predicted positive outcomes to the total of correctly predicted negative outcomes. Recall quantifies how well the model can recognize all true positive instances [23].

$$Sensitivity = \frac{TP}{TP+FN} \quad (9)$$

The Table 2. Compares the performance of a model on training and testing data. The performance analysis for different training and testing ratios reveals a clear trend in accuracy, sensitivity, and specificity. With a training to testing ratio of 45:55, the accuracy is 68.79%, the sensitivity is 83.46%, and the specificity is 57.78%. Increasing the training ratio to 55:45 improves the accuracy to 77.88%, the sensitivity to 87.92%, and the specificity to 67.95%. Finally, at a training to testing ratio of 75:25, the highest performance is observed with an accuracy of 96.79%, a sensitivity of 98.34%, and a specificity of 98.63%.

Table 2: Testing and Training performance analysis

Training/Testing	Accuracy	Sensitivity	Specificity
45/55	68.79	83.46	57.78
55/45	77.88	87.92	67.95
65/35	82.67	93.37	87.45
75/25	96.79	98.34	98.63

The classification method presented in this work achieves a superior performance compared to previous methods in Table.3. The analysis of various methods shows varying levels of accuracy, sensitivity, and precision. Method [6] attains an accuracy of 92.53%, a sensitivity of 91.36%, and precision of 96.36%. Method [16] has an accuracy of 85.71%, a sensitivity of 86.16%, and precision of 98.34%. Method [17] reports lower values with an accuracy of 76.22%, a sensitivity of 78.0%, and a precision of 76.0%. In comparison, the current work achieves the highest performance, with an accuracy of 99.54%, sensitivity of 99.85%, and precision of 99.64%. Fig.4. shows the comparative performance of proposed method.

Table 3. Comparison with previous classification methods

Methods	Accuracy	Sensitivity	Precision
[6]	92.53	91.36	96.36
[14]	97.75	98.87	98.57
[16]	85.71	86.16	98.34
[17]	76.22	78.0	76.0
This work	99.54	99.85	99.64

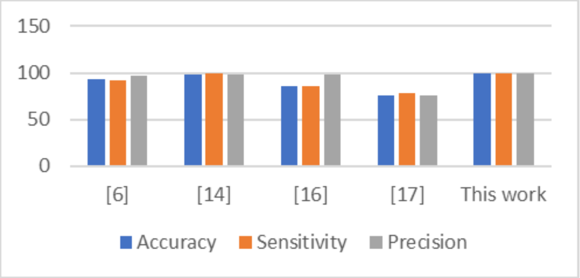

Fig.4. Comparative performance of proposed method

5. Conclusion

The development and integration of machine learning and data mining techniques offer a promising avenue for revolutionizing the management of heart disease. Through the utilization of LSTM networks, PCNNs, and standardized treatment protocols derived from extensive data analysis, this framework presents a comprehensive approach to addressing key aspects of heart disease prediction, treatment recommendation, and side effects management. The LSTM-based heart disease prediction model demonstrates the potential to accurately forecast cardiac events by leveraging temporal dependencies within patient health records. By effectively capturing sequential patterns and trends, this model equips clinicians with valuable insights for early intervention and risk mitigation. The PCNN-based treatment recommendation system complements traditional approaches by offering personalized therapy suggestions tailored to individual patient profiles. Through the recognition of complex patterns in patient data and synchronization of neuron responses, this system provides clinicians with valuable decision support, enhancing treatment efficacy and patient outcomes. Furthermore, the implementation of standardized treatment protocols derived from data mining of clinical records contributes to more effective side effects management, reducing the burden of adverse reactions and improving patient adherence to treatment regimens. In combination, these components form an integrated data mining and machine learning framework that holds significant potential for transforming heart disease care. By providing clinicians with actionable insights derived from comprehensive data analysis, this framework facilitates informed decision-making, enhances patient care, and contributes to the optimization of healthcare delivery in the management of heart disease.

Author contributions

Uma K: Conceptualization, Methodology, Writing-Original draft preparation.

Prof. Hanumanthappa M: Reviewing, Editing, Finalizing the paper.

Conflicts of interest

The authors declare no conflicts of interest.

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