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Kenyan Sign Language Recognition Using Ensemble Method

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Abstract: *The interaction between two or more people is called communication. It may be performed by word, by a written paper, by gestures like hand and head movements, by facial expression, by lips movement. Social inclusion heavily relies on communication, but there still exist severe obstacles to it as very little is known or translated to the Kenyan Sign Language (KSL). Unlike the American or Indian Sign Language, KSL has its own linguistic and cultural systems that cannot be identified by generic recognition systems. This work counters such issues by creating an ensemble machine-learning approach to KSL recognition that integrates the feature-extraction capability of Convolutional Neural Networks (CNN) with the classification strength of k-Nearest Neighbors (KNN). The model was preprocessed, augmented, and annotated using a curated dataset of 8,898 labeled KSL images obtained via Kaggle, in order to increase diversity and decrease noise. Gesture images were fed to the CNN component that extracted high-level spatial features, and then the KNN classifier used the same embeddings to make similarity-based decisions. In order to improve accuracy and reliability in relation to misclassification, a stacking ensemble method was used to combine the two models. Performance on the test set was evaluated using evaluation metrics such as precision, recall, F1-score and confusion matrices. The ensemble model was more accurate (70.32) than standalone classifiers and it was also found to have better recognition of the more complicated KSL gestures. These findings highlight how ensemble learning can be used to overcome communicative barriers between the Deaf and hearing populations in Kenya. The paper offers a technological solution to real-time KSL recognition, as well as provides a base to conduct further studies on larger and more varied datasets and gesture recognition in dynamic time. Finally, the work leads to the social inclusion process because it allows the use of convenient communication means that empower Deaf individuals and facilitate equal access to education, health, and everyday life.*

Key Words: *Kenyan Sign Language (KSL), Ensemble Learning, Convolutional Neural Network (CNN), K-Nearest Neighbors (KNN), Sign Language Recognition*

I.INTRODUCTION

In Kenya, the main communication language used by the deaf people is Kenyan Sign Language (KSL). Instead, KSL is an entirely different lingo-system with its own grammatical structures and its own vocabulary, compared to other spoken languages, such as Swahili or English. Nonetheless, there is little awareness and use of KSL especially among parents of children with hearing impairments who should instill sign language in their children at an early age but unfortunately, do not know how. The gap will continue to create communication barriers and block social inclusion of deaf individuals.

Hearing impairment is becoming common around the world. According to the World Health Organization (2021), more than 5% of the world population is estimated to require hearing rehabilitation services and this percentage is expected to grow to over 700 million by 2050. Not only does untreated hearing loss negatively affect people by increasing stigma, isolation, and diminishing opportunities, but it also imposes an estimated healthcare cost of approximately 980 billion USD and lost productivity, plus social expenses on the global economy annually. The 2019 census in Kenya indicated that there were over 150,000 people with hearing impairment, a factor dwarfing the scale and magnitude of the problem.

Whereas sign languages are different in various regions owing to cultural and environmental factors, techno-logic interventions are being gradually being implemented across all parts of the world to better accessibility. The development of artificial intelligence (AI), machine learning (ML), and computer vision technologies is changing the possibility to create interactive systems that can convert sign language into spoken or written text. Modern devices such as cochlear implantations, real time classroom interpretation and text facilities provide incomplete support and are not enough to overcome communication barriers entirely.

There have been encouraging moves on the local level. The Kenyan Sign Language and Technology (KSLT) research team, based at the C4DLab laboratory at the University of Nairobi, has been foremost in seeking to incorporate KSL with new technologies. An example that has used TensorFlow, OpenCV, and transfer learning to train a KSL recognition model is Wanjala (2023). Although the above findings are promising, a small vocabulary, restricted experimental data, and deficient frameworks capable of generalizing to real-life settings have characterized the extant literature to date.

II.LITERATURE REVIEW

Sign language recognition (SLR) studies have been receiving considerable momentum over the past few years, led by developments in computer vision, artificial intelligence and machine learning. In general, the available literature uses either a vision based or sensor based approach. In vision system, cameras and deep learning models are used to recognize and detect hand motions; in sensor-based, a wearable computer is used to measure the motion and muscle movements.

Computer vision techniques have been used successfully in reading hand gestures or speech. Previous contributions included work by Dabre and Dholay and Bantupalli and Xie, who implemented image processing and neural networks to decode sign gestures into a written or spoken form of language [3, 5]. Subsequent models improved in terms of the use of convolutional neural networks (CNNs) and transfer learning. Greater than 99 percent accuracy in recognition of fixed signs was indicated by Ankita and Parteek (2020), and Vijeeta (2022) and Rama et al. (2024) indicated CNN-based solutions that can be applied to produce strong recognition under various circumstances. Ensemble learning has also been studied more recently, with Samarth and Kabir (2023) implementing Inception V3 and ResNet 101 to reach 97.24% accuracy and Peeyusa et al. (2023) stacking models to reach over 99% accuracy.

These efforts are complemented by sensor-based efforts that detect fine-grained motion information using wearable devices. Rinki et al. (2023) trained multi-sensors data in an ensemble CNN system on Indian Sign Language, with a 94.2 percent accuracy. Ang et al. (2023) have shown that data gloves with Random Forest classifiers achieve higher accuracy of 97.58%. Flexible strain sensors (Yuxuan et al., 2023) and electromyogram-based solutions (Rinki and Arun, 2021) are factors that justify why sensor driven models can be almost guaranteed to achieve high accuracy on sign recognition tasks.

Though they have advanced, limited research has been done relating to Kenyan Sign Language (KSL). Wanjala (2023) created a KSL recognition model on TensorFlow and OpenCV, but Ngaruiya and Wanjiku (2021) proposed an embedded system installed with sensors and KNN to complete the sign-to-speech conversion. Nevertheless, the majority of these models are based on small or foreign datasets, emphasize on still gestures, and no ensemble designs that adapt to the Kenyan context are available. Further, a good number have been experimented in controlled settings, restricting their use in actual applications.

There is a glaring gap identified in the reviewed literature since although more ensemble methods and deep learning architectures succeeded in American and Indian Sign Language recognition, their implementation on KSL has not been tested extensively. This paper thus attempts to fill this gap by developing and testing an ensemble learning system combining CNN and KNN to improve the accuracy, stability, and context sensitivity of Kenyan Sign Language recognition.

III.METHODOLOGY

In this work, an experimental research design was used to design and test an ensemble model of Kenyan Sign Language Recognition (KSLR). The method combines computer vision methods and ensemble machine learning with a Convolutional Neural Network (CNN) to extract features and a K-Nearest Neighbors (KNN) to ultimately classify the gesture.

3.1. Dataset Acquisition and Sampling

The data was obtained in the form of a publicly-available Kaggle repository of 8,898 annotated Kenyan Sign Language gesture images, both stationary sign anatoms and typical words, e.g., Mosque, you, me, and church. Images were normalized and made standardized so that they have the same dimensions. The training and test data were selected using a simple random sampling method based on probability to balance representation of each type of gesture.

3.2. Preprocessing and Feature Extraction

Raw pictures were subjected to some preprocessing to improve the performance of the models. Filtering was done to reduce noise and background subtraction was done through the use of Gaussian averaging. Pictures were scaled to 64 x 64 pixels and brought to a [0,1] range. Robustness was enhanced by data augmentation techniques (rotation, flipping, brightness adjustment etc.). Annotation was performed with labelImg and video capture and image processing were performed with OpenCV. A CNN was used to extract features, which automatically learned hierarchies of features across space to generate dense embed-ling vectors, which were used to classify.

3.3. Model Construction and Training

This was an ensemble architecture based on a stacking framework. The CNN was used as the initial ex-tractor of high-level embedding of the gesture images. The embeddings were then categorized by a KNN model based on the Euclidean distance, the best value of k obtained by cross-validation. The ensemble fusion was a weighted soft-voting system that combined CNN probability outputs and KNN vote distributions to combine the respective strengths of the two algorithms.

3.4. Model Evaluation

Model testing was done by dividing the data into training (80) and test (20) sets. Measures of performance were based on accuracy, precision, recall, F1-score, and confusion matrix. The ensemble model achieved a classification result of approximately 70.03 that is superior to that of individual classifiers and shows that deep learning is beneficial in addition to in-instance-based classifiers in KSL recognition.

3.5. Ethical Considerations

The data necessary in this study were either found in the open-source repository or had the proper license. To ensure confidentiality of participants, im-ages were anonymized, and facial features had to be blurred. The study was conducted according to ethical considerations as recommended by the review board of Cooperative University of Kenya with the recognition that prior studies informed the study methodology.

IV.MODEL DESIGN

4.1. Introduction

Kenyan Sign Language Recognition (KSLR) ensemble architecture was developed in a way that combined strengths of both Convolutional Neural Networks (CNN) and K-Nearest Neighbors (KNN). It was designed to be robust, flexible and interpretable, overcoming the drawbacks of single-modelling designs.

4.2. Data Acquisition and Preparation

The design process started by the selection of a dataset of 8,898 annotated images of Kenyan Sign Language gestures downloaded on Kaggle. It contained alphabets and frequently used words like church, mosque, me, you etc. All the images were resized to 64 x 64 pixels in order to be consistent. The pixel values were brought to the [0,1] range, and data augmentation techniques were applied to the data (flipping, rotation, change of brightness) to make it less biased and less prone to overfitting. Isolating hand regions was also done using background subtraction.

To eliminate bias in future tests, a stratified split was used to split the dataset into training (80) and testing (20) sub-sets using a balanced class distribution.

4.3. Feature Extraction with CNN

The CNN was designed as the primary feature extractor. The architecture consisted of three convolutional blocks, each incorporating convolutional layers with ReLU activation, batch normalization, and max pooling. These blocks captured progressively complex features, with the initial layers focusing on basic patterns such as edges and textures, and deeper layers representing higher-order hand configurations.

The final convolutional output was flattened and passed through a dense embedding layer with 256 units. Dropout regularization at 0.5 was introduced to mitigate overfitting, while the Adam optimizer (learning rate = 0.001) was employed for efficient gradient-based optimization.

4.4. Gesture Classification with KNN

After the feature extraction step, CNN generated embeddings were then classified with KNN. Similarity between input and stored embeddings were measured with Euclidean distance metric. Experiments of cross-validation suggested that the best and stable classification performance was with k=5. The non-parametric design of KNN was flexible in the sense that it was able to adapt to new inputs without the need to re-train.

4.5. Ensemble Integration Strategy

There was a stacking ensemble between CNN and KNN. In this architecture CNN was used as the feature extractor and KNN was used as the decision layer. In the inference, KNN was used to classify CNN embeddings. A mecha-voting soft-voting system was utilized that combined predictions which weighted CNN results 65 percent and KNN 35 percent. This method used CNN to learn hierarchical repetitions but left KNN to make refinement of predictions on less frequent or ambiguous gestures.

4.6. System Interaction Flow

Use-case and state-chart diagrams were used to present the functional design of the system. The use-case diagram was used to specify the relationships between the key actors, such as the Deaf signers, hearing users, developers, administrators, and dataset curators. The entire recognition process, i.e. image capture and pre-processing, CNN feature extraction, KNN classification, ensemble fusion and final translation output was mapped on the state-chart diagram. It included user feedback loops that allow the system to improve itself.

4.7. Design Outcome

The model design established a framework that balances CNN’s capacity for automatic feature learning with KNN’s strength in similarity-based reasoning. This combination addressed the weaknesses of individual models and supported the development of amore generalizable and interpretable system. The design ensured readiness for real-world deployment by emphasizing robustness across diverse gestures, signers, and environmental conditions.

V.MODEL DEVELOPMENT

5.1. Introduction

Kenyan Sign Language Recognition (KSLR) ensemble model development was orchestrated into a systematic process whereby a dataset is prepared, features are extracted, gestures classified and ensembles combined. The methodology focused on rigor of the approach to provide strength, repeatability and generalizability.

5.2. Development Environment

The implementation has been carried out in a Python ecosystem with Jupyter Notebook 6.5.3 as the interactive development environment. The deep learning framework used in the convolutional neural network was implemented with TensorFlow (version 2.12) whereas image preprocessing and manipulation were performed with OpenCV (version 4.7). The K-Nearest Neighbors classifier was fitted with scikit-learn (version 1.4) and annotated the data set with LabelImg. Git was used as a tool to maintain reproducibility in all experiments.

The computing device was a Spectra laptop with 16GB memory, 1TB SSD hard disk and an inbuilt 8GB graphical card. This setup offered sufficient resources to model training, hyper parameter optimization, and large-scale dataset processing, besides allowing efficient execution of training epochs.

5.3. Dataset Collection and Preprocessing

It was a dataset of 8,898 labelled images of Kenyan Sign Language gestures. The collection consisted of alphabets, numbers and some common lexical items like church, mosque, stop, me, you etc. All the images were reduced to 64 x 64 pixels. Preprocessing included: pixel intensities were normalized to the [0,1] range, pixel intensities were padded by flipping, rotation, and brightness corrections, and background sub-traction to extract the hands.

Labeling was done using the LabelImg tool to provide consistency in labeling between the classes of gestures. A stratified split was used to divide the dataset into training (6,250 images) and testing (2,648 images) and maintain the balance of classes as well as make the dataset representative.

5.4. Feature Extraction with CNN

Feature extraction was achieved through a convolutional neural network consisting of three convolutional blocks. Each block comprised convolutional layers with ReLU activation, batch normalization, and max pooling. Initial layers captured low-level features such as edges and contours, while deeper layers extracted high-level abstractions corresponding to hand shapes and orientations.

The network output was flattened and passed through a dense embedding layer of 256 units. Dropout regularization (0.5) was employed to mitigate overfitting. Training utilized the Adam optimizer with a learning rate of 0.001, and early stopping was applied to prevent unnecessary iterations once validation performance plateaued.

5.5. Classification with KNN

The CNN generated embeddings were then classified by a K-Nearest Neighbors classifier. Similarity was used as Euclidean distance. The best neighbor size was determined to be k=5 using cross-validation since the neighbor size of 5 provided sufficient classification accuracy and low computational cost. Non-parametricity of KNN enabled it to be adapted to new input cases without being re-trained, offering both flexibility and robustness to deal with rare or ambiguous signs.

5.6. Ensemble Integration

CNN was stacked with KNN in an integration architectural approach. The CNN was the feature extractor and KNN was the final classifier. The KNN classifier was fed by CNN embedding of test images during inference. The combination of CNN and KNN results with weights of 65% and 35 was used as a weighted soft-voting method. This weighting resulted in CNN keeping its strength in identifying frequent gestures and left KNN to solve difficult or less frequent cases.

5.7. Model Evaluation

Performance measures used were accuracy, precision, recall, F1-score and confusion matrix. The ensemble currently reached accuracy of about 70.32%, better than CNN-only and KNN-only baselines. The overall performance was significantly high when it came to working with the static gestures and more challenging when working with dynamic gestures since the dataset was static.

5.8. Outcome

The growth process produced CNN-KNN ensemble model, which can identify Kenyan Sign Language gestures and convert them into an English text more robustly and explainably. The CNN feature learning hierarchy and CNN instance-based reasoning complemented each other to generate greater generalization in multimodal classes of gestures. Despite the drawbacks for dynamic gestures, the model proved the possibility of ensemble learning sign language recognition in the Kenyan environment and gave the basis on which it can be improved in the future.

VI.RESULTS AND DISCUSSION

6.1. Introduction

The growth process produced CNN-KNN ensemble model, which can identify Kenyan Sign Language gestures and convert them into an English text more robustly and explainably. The CNN feature learning hierarchy and CNN instance-based reasoning complemented each other to generate greater generalization in multimodal classes of gestures. Despite the drawbacks for dynamic gestures, the model proved the possibility of ensemble learning sign language recognition in the Kenyan environment and gave the basis on which it can be improved in the future.

6.2. Quantitative Results

The ensemble achieved an overall accuracy of 70.32% on a balanced 9-class validation problem comprising 1,250 images. Macro-level metrics indicated strong and consistent performance across classes: precision = 0.711, recall = 0.703, and F1-score = 0.704. Weighted averages were nearly identical, confirming that the results were not disproportionately influenced by any single dominant class.

6.3. Class-Wise Performance

Class-level analysis highlighted both robust recognition and notable weaknesses. Several classes performed strongly, with **F1-scores in the mid-70s to low-80s:**

1) **Class 6**: Recall 77% (107/139 correct),
2) **Class 5**: Recall 76% (106/139 correct),
3) **Class 3**: Recall 76% (105/139 correct),
4) **Class 2**: Recall 75% (103/138 correct),
5) **Class 4**: Recall 74% (103/139 correct).

Conversely, weaker performance was observed in specific classes:

1) **Class 0**: Recall 52% (72/139 correct), with nearly half of the examples misclassified,
2) **Class 1**: Recall 68% (94/139 correct),
3) **Class 7**: Recall 65% (90/139 correct).

Precision issues were most pronounced in Class 8 (precision ≈ 0.59), where the model frequently mislabeled samples as Class 8, and reducing reliability.

6.4. Confusion Matrix Analysis

The confusion matrix (Figure 7.1) revealed clear misclassification patterns. Several directional errors dominated:

1) **Class 0 → Class 1:** 31 cases (21.6% of Class 0 samples),
2) **Class 2 → Class 3:** 22 cases (15.2%),
3) **Class 4 → Class 8:** 20 cases (10.1%), and Class 8 → Class 4: 13 cases (9.4%),
4) **Class 7 → Class 8:** 15 cases (10.1%),
5) **Class 5 → Class 1:** 15 cases (10.1%),
6) **Class 6 → Class 8:** 12 cases (8.6%),
7) **Class 1 → Class 7:** 10 cases (7.9%).

These patterns demonstrate the difficulty in distinguishing visually similar gestures and highlight areas where additional dataset curation or architectural enhancements are required.

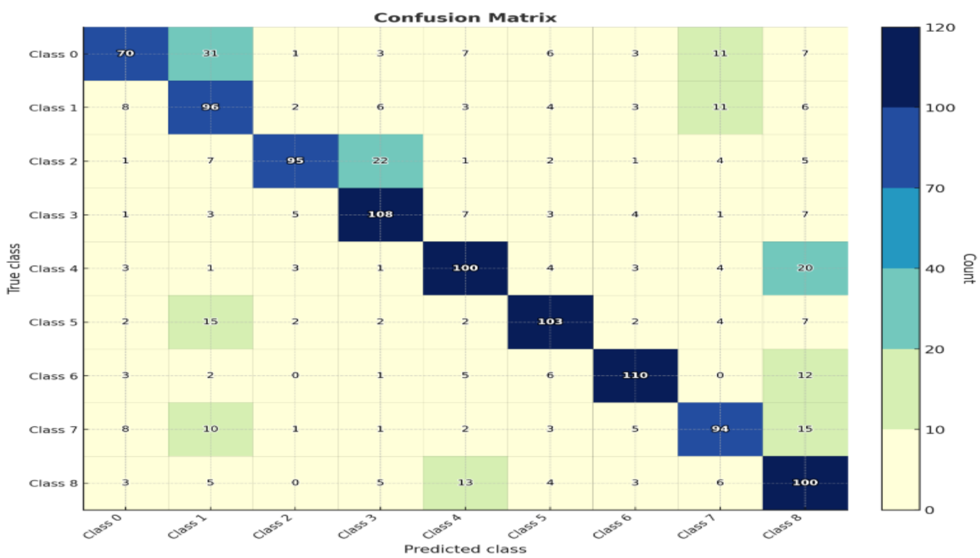

Figure 1: Confusion Matrix of CNN–KNN Ensemble on KSLR Validation Set.

6.5. Comparative Insights

In independent comparison CNN had good performance in terms of feature extraction but was likely to misclassify visually similar gestures. KNN was less scalable as an independent model and was more resistant to rare cases. The ensemble approach alleviated these weaknesses by weighted soft voting (65% CNN and 35% KNN) and provided a better balance and strength.

The 70 percent performance of the KSLR model, compared to international standards like ASL and ISL recognition systems which report over 90 percent accuracy, highlights the difficulties of smaller datasets, lack of signer diversity, and local linguistic diversity.

6.6. Implications

The results affirm the feasibility of ensemble learning for KSLR. The system demonstrated real-time translation potential and robustness for static gestures. However, recognition of dynamic gestures remains a challenge, suggesting that future work should incorporate temporal models such as LSTMs or transformers. Additionally, expanding the dataset to include diverse signers, lighting conditions, and environmental contexts is crucial to improving generalizability.

6.7. Limitations

Key limitations identified include:

1) Reliance on static gesture images, limiting recognition of motion-dependent signs,
2) Modest dataset size compared with international benchmarks, reducing generalization capacity,
3) Sensitivity of the ensemble weighting scheme, requiring careful tuning to balance CNN and KNN contributions.

6.8. Summary

Overall, CNN-KNN ensemble performed rather well, and balanced macrolevel results were obtained (precision = 0.711, recall = 0.703, F1 = 0.704) and accuracy was 70.32. The confusion matrix also identified strengths in being able to identify dominant visual cues and weaknesses in the inability to process visually similar or ambiguous gestures. The findings support the applicability of ensemble learning to Kenyan Sign Language recognition and can be used in the future as a robust foundation to scale up to larger data sets, add time-dependent models, and further scale up to a real-world application.

VI.CONCLUSION AND RECOMMENDATIONS

7.1. Conclusion

The aim of this study was to design, develop and test an ensemble model of Kenyan Sign Language Recognition (KSLR) that would overcome the communication barriers of the Deaf community in Kenya. The model successfully used deep feature extraction and in-stance-based classification together by stacking Convolutional Neural Networks (CNN) and K-Nearest Neighbors (KNN) in a stacking ensemble framework.

The model had a total validation accuracy of 70.32, and at the macro level, it had a precision of 0.711, a recall of 0.703, and an F1 score of 0.704. The confusion matrix analysis validated trustworthy identification of some of the gesture classes, and pointed at challenges with similar-to-each other signs. These findings highlight the viability as well as constraints of utilizing ensemble learning on KSLR. The result is highlighted in the context of the peculiarities of re-source constrained settings (small dataset and sample size, heterogeneity of signers, and linguistic variations) when compared to foreign systems such as ASL and ISL recognition systems where more accurate rates are reported. However, the article remains a valuable contribution since it provides KSLR with a reference framework with which it can demonstrate that the power and explanatory quality of the ensemble learning exceeds the performance of the individual models.

Finally, the research article appears to confirm that ensemble models are an interesting way to go in the real-world application of KSLR to education, health, and social inclusion.

7.2. Recommendations

Based on the findings, the following recommendations are proposed:

1. Dataset Expansion and Diversification

Further research is needed to develop more extensive and more diverse datasets of Kenyan Sign Language. These involve the input of signers of different age groups, gender and regional dialects. The model generalizability will also be improved because data will be collected in various lighting conditions and environments.

2. Integration of Dynamic Gesture Recognition

Most KSL signs are dynamic in nature, so the future models must be built with temporal learning structures (Long Short-Term Memory (LSTM) networks, 3D CNNs, or transformer-based models). These would provide motion dependencies which cannot be modeled by static image models.

3. Optimization of Ensemble Strategies

Although this weighted soft voting did better, more research is needed about adaptive weighting processes or meta-learners in ensemble structures. These may adjust dynamically contributions to models depending on their characteristics.

4. Real-Time System Deployment and Feedback Loops

In order to make it usable in real life, real-time deployment testing needs to be done. The addition of feedback mechanisms within the system giving users the ability to correct false classifications will provide the system with continuous learning and fine-tuning over time.

5. Cross-Linguistic and Cross-Modal Extensions

It would be beneficial to expand the method to other sign languages in Africa and add multimodal inputs (e.g. depth sensing, glove sensors, or sounds as a bilingual communication method) to expand applicability and enhance system robustness.

6. Policy and Accessibility Integration

It is necessary to coordinate the efforts of educational institutions, Deaf organizations, and policymakers so that KSLR technologies meet the objectives of accessibility. These types of partnerships would facilitate the process of integrating the system into classes, interpretation services and assistive technologies.

7.3. Final Remarks

This study shows how ensemble learning can be useful in the development of Kenyan Sign Language recognition. Although there are still problems, especially when using dynamic gestures and scaling datasets, the research offers an excellent background on the next level of innovation. The work helps to support the bigger objective of inclusive communication technologies empowering the Deaf community and promoting social equity in Kenya and elsewhere by connecting technical progress with societal demand.

Abbreviations

KSL	Kenyan Sign Language
CNN	Convolutional Neural Networt
KNN	K-Nearest Neighbors
KSLR	Kenyan Sign Language Recognition
AI	Artificial Intelligence
ML	Machine Learning
ISL	Indian Sign Langauge
ASL	American Sign Langauge

Conflicts of Interest

No Conflict of interest

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