Journal papers summary

Paper-1

1. Title of the Paper:

- Detection of Diseases on Dental Periapical Radiographs Using Deep Convolutional Neural Networks: Evaluation Across Disease Categories, Severity Levels, and Training Strategies

2. Area of Work:

- Dental radiography, specifically the application of deep learning (CNNs) for disease detection on periapical radiographs.

3.Dataset:

- Clinical dental periapical radiographs used for training and validation. Specific details about the size or source of the dataset are not mentioned in the abstract.

4. Methodology/Strategy:

- Deep CNNs with Region Proposal Techniques: Developed and trained deep convolutional neural networks (CNNs) equipped with region proposal techniques for disease detection.

5. Algorithm:

- Deep convolutional neural networks (CNNs) were used for the detection of diseases (decay, periapical periodontitis, and periodontitis) on dental periapical radiographs.

6. Result/Accuracy:

- Precision and recall for detecting lesions ranged generally between 0.5 and 0.6 for each disease type.

- Performance metrics (IoU, precision, recall, AP) were significantly influenced by the training strategy, disease category, and severity level ($P<.001$).

- Net A performed similarly to the baseline, while Net B and Net C showed slight improvements over baseline under certain conditions ($P<0.05$).

7. Advantages: - Potential for accurate disease detection on dental periapical radiographs using deep learning.

- Can handle complex image data and provide consistent performance once trained.

8. Limitations:

- Specific details about the dataset size or diversity are not provided.

- The study does not discuss external validation on different datasets or clinical settings.

- Performance variations across different types of dental radiographs (e.g., intraoral versus panoramic) are not explored.

9. Future Proposal:

- Conduct further research to refine and optimize the deep learning models for better accuracy, especially for mild and moderate disease levels.

- Explore the integration of real-time decision support systems in clinical workflows.

- Investigate the feasibility of deploying the developed models in diverse clinical settings to validate their robustness and generalizability.

Paper-2

1. Title of the Paper:

- "Detection of Periapical Radiolucency's on Panoramic Radiographs: A Comparative Study of Deep Learning Algorithm and Oral Maxillofacial Surgeons"

2. Area of Work:

- Dental radiology, specifically the detection of periapical radiolucency on panoramic radiographs.

3. Dataset:

- The study used a curated dataset of 2902 de-identified panoramic radiographs.

4. Methodology/Strategy:

- Methodology:

  - Developed and trained a deep learning algorithm to detect periapical radiolucency.

  - Assessed the performance of 24 oral and maxillofacial (OMF) surgeons in comparison to the algorithm.

- Strategy:

  - Used the dataset to train and validate the deep learning algorithm.

  - Evaluated both surgeons and the algorithm based on diagnostic metrics (PPV, TPR, precision, and F1 score).

5. Algorithm:

- A predictive deep learning algorithm was developed for the detection of periapical radiolucency's on panoramic radiographs.

6. Result/Accuracy:

- Surgeons:

  - Mean PPV: 0.69 (±0.13)

  - Mean TPR: 0.51 (±0.14)

- Deep Learning Algorithm:

  - Average precision: 0.60 (±0.04)

  - F1 score: 0.58 (±0.04)

  - Mean PPV: 0.67 (±0.05)

  - Mean TPR: 0.51 (±0.05)

- The algorithm outperformed 14 out of 24 OMF surgeons in the cohort.

7. Advantages:

- Provides consistent performance in detecting periapical radiolucency's.

- Potentially reduces diagnostic errors compared to human variability.

- Can analyse large volumes of data quickly.

8. Limitations:

- Evaluated on a limited dataset; generalizability to different populations or settings is unclear.
- The study did not explore reasons behind individual surgeon variability.
- Ethical and legal considerations related to the use of AI in healthcare.

9. Future Proposal:

- Conduct further research and validation in larger and more diverse patient cohorts.
- Refine the algorithm to improve accuracy and robustness.
- Investigate real-time implementation and integration into clinical workflows.
- Explore the potential for AI to assist in treatment planning and patient management beyond diagnosis.

Paper-2

1.Title of the paper:

Not explicitly mentioned, but likely related to automatic dental X-ray classification (e.g., "Automatic Classification of Dental X-ray Images using Convolutional Neural Networks").

2.Area of work:

Medical image analysis, specifically dental X-ray classification.

3.Dataset:

Dental X-ray images categorized into cavity, filling, and implant.

4.Methodology/Strategy:

Convolutional Neural Network (CNN) with transfer learning from a NASNet model and data augmentation techniques.

Algorithm:

NASNet (pre-trained CNN architecture).

5.Result/Accuracy:

96.51% accuracy with data augmentation.

93.36% accuracy without data augmentation.

6.Advantages:

Improved efficiency compared to manual analysis by dentists.

Increased objectivity and potentially higher accuracy.

7.Limitations:

Reliant on the quality and size of the training dataset.

Potential for errors, especially with rare or unclear cases.

8.Future Proposal:

Expand the dataset for improved performance.

Explore more complex deep learning architectures.