# Paper Review: Ordinal Learning: Longitudinal Attention Alignment Model for Predicting Time to Future Breast Cancer Events from Mammograms

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## 1. SUMMARY

This paper discusses a new ordinal learning method named OA-BreaCR which outperforms other methods for determining the time-to-future event for breast cancer diagnosis for risk assessment for breast cancer patients. Time-to-future basically means not only assessing the risk of having breast cancer but also predicting how long in the future it will take for breast cancer to develop in a person at a certain risk level.

Being able to have this more precise risk assessment will enhance breast cancer screening and prevention efforts.

## 2. STRENGTHS

- This method addresses the weakness of transformer-based approaches which are unsupervised. The weakness is that these transformer-based methods only use past data to predict present diagnosis but doesn't explain changes over time. Also, transformer-based methods may introduce biases from taking multiple breast images over time due to the breast being compressed during the imaging process. This new method monitors changes over time to determine breast cancer risk
- Method is tested and trained on a large amount of images (170,000+) on the same 9300 women over a period of nearly 2 decades. This seems like a sufficiently large dataset over a long enough period of time to establish a relationship between time and risk of breast cancer.
- This method uses a relatively light-weight ResNet-18 model with pretrained weights to do training and inference. This means that the model can be used on relatively cheap consumer GPUs and results can be tested and reproduced and even fine-tuned over time by other researchers or doctors.

  Specific details of image pre-processing are also given which further allow reproducibility and use in real world settings.

## 3. WEAKNESSES

- How effective in the real-world is predicting breast cancer based purely on medical images over time? This seems like a very narrow way of predicting a disease that is relatively complex. Other factors might come into play over time such as diet, weight gain, body composition, etc… that could be used as inputs to the model to provide a better risk assessment then just the images alone which can have a lot of variability and might not explain the entire picture of the human being.
- Although using a deep learning method, i.e Resnet-18 is good for purely using medical images to predict breast cancer risk with time…. A Transformer model might be better for factoring other types of information that are not image related and combining them with the medical images for a more holistic and stronger predictive model.

## 4. TECHNICAL EXTENSIONS

- A future extension would be to apply this time to cancer model for other types of cancer or even to heart disease which is the most common disease in the United States.
- Extend the time to diagnosis model to include not just medical-imaging but also other factors such as weight, body composition, race, age, etc… to create a more holistic model

## 5. OVERALL REVIEW

The concept of  building a risk prediction model by factoring images of the same person over time to predict time to cancer is a useful concept that will provide better risk assessment then to not have this information. Another benefit is that this timeframe information can provide more immediacy to the person and doctor that needs the prediction so that action can be taken more quickly and with greater dedication further reducing the chances of the disease.

Another strength is that this model can be run of relatively cheap consumer GPUs. Although training was done on a single A600 GPU, inferencing, can be done on less powerful hardware meaning that a capital-strapped hospital need not make a significant financial investment in a workstation computer in order to have more accurate screening and risk assessment for breast cancer.

However for a complex disease such as cancer, other information should be factored in to provide a more accurate time-to-cancer diagnosis such as lifestyle factors, and body composition.