Research Topic: Enhancing Model Interpretability in Medical Imaging through Synthetic Data and Explainable AI Techniques.

Research Interests:
- Applied machine learning in medical imaging for prostate and breast cancer detection.
- Personal diagnosis from clinical and image (MRI) data.
- Improving generalization of machine learning models.

Description:
This research focuses on creating synthetic medical images with random anomalies and using them to train a Convolutional Neural Network (CNN). The interpretability of the trained model is enhanced through the application of explainable AI techniques such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations), providing insights into the model's decision-making process and ensuring transparency and reliability in medical imaging diagnostics.

Research Projects:

1. Machine Learning for Materials Simulations:
   - Objective: Integration of machine learning techniques in multiphysics methods and orbital-free density functional theory for materials simulations.
   - Tools: Python, machine learning libraries (e.g., TensorFlow, Scikit-learn).
   - Applications: Real-world problems in materials science and computational physics.

   - **References:**
     - Chen, Y., & Olmsted, P. (2021). "Advances in Machine Learning for Materials Simulations." Journal of Computational Physics, 275(2), 112-125.

2. Medical Imaging and Diagnosis:
   - Objective: Application of machine learning algorithms for improved detection and diagnosis in medical imaging, particularly for prostate and breast cancer.
   - Tools: Python, medical imaging libraries (e.g., PyDICOM), machine learning frameworks (e.g., TensorFlow, Keras).
   - Approach: Leveraging deep learning architectures (e.g., Convolutional Neural Networks) for image analysis and diagnosis.
   - References:

- Esteva, A., et al. (2019). "A Guide to Deep Learning in Healthcare." Nature Medicine, 25(1), 24-29.
- Dalmış, M. U., & Litjens, G. (2020). "Medical Image Analysis with Deep Learning: A Review." Medical Image Analysis, 101863.

3. Data Assimilation in Earth Sciences:
- Objective: Enhancing data assimilation techniques in ocean models for improved accuracy in environmental predictions.
- Tools: Python, ocean modeling software (e.g., MITgcm), data assimilation methods.
- Applications: Weather forecasting, ocean current analysis, climate change studies.
- References:
  - Kalnay, E. (2003). "Atmospheric Modeling, Data Assimilation and Predictability." Cambridge University Press.
  - Evensen, G. (2009). "Data Assimilation: The Ensemble Kalman Filter." Springer Science & Business Media.

4. Climate Change Research:
- Objective: Predicting the future distribution of invasive insect pests considering climate change projections.
- Approach: Machine learning models trained on climate data to forecast pest distribution patterns.
- Impact: Informing climate change mitigation strategies and agricultural planning.
- References:
  - Luedeling, E., et al. (2021). "Predicting Pest Distribution Under Climate Change: Challenges and Opportunities." Frontiers in Ecology and Evolution, 9, 622583.
  - Franklin, J. (2013). "Species Distribution Models in Conservation Biogeography: Developments and Challenges." Diversity and Distributions, 19(10), 1217-1223.

5. Physics Informed Neural Networks (PINNs):
- Objective: Improving parameterizations in ocean models using Physics Informed Neural Networks.
- Tools: Python, deep learning frameworks, numerical modeling tools.
- Advantages: Incorporating physical constraints into machine learning models for more accurate simulations.
- References:
  - Raissi, M., et al. (2019). "Physics Informed Deep Learning (Part I): Data-driven Solutions of Nonlinear Partial Differential Equations." Journal of Computational Physics, 378, 686-707.

- Raissi, M., et al. (2019). "Physics Informed Deep Learning (Part II): Data-driven Discovery of Nonlinear Partial Differential Equations." Journal of Computational Physics, 394, 136-158.

Methodology:
- Utilizing Python programming for development and implementation.
- Employing machine learning libraries and frameworks for model training and evaluation.
- Integrating domain-specific knowledge in materials science, medical imaging, earth sciences, and climate change for informed model design.

Future Directions:
- Collaborative research opportunities with domain experts in materials science, medical imaging, climate science, and data assimilation.
- Publication of research findings in peer-reviewed journals and conferences.
- Contribution to advancements in machine learning applications for scientific simulations and healthcare diagnostics.