



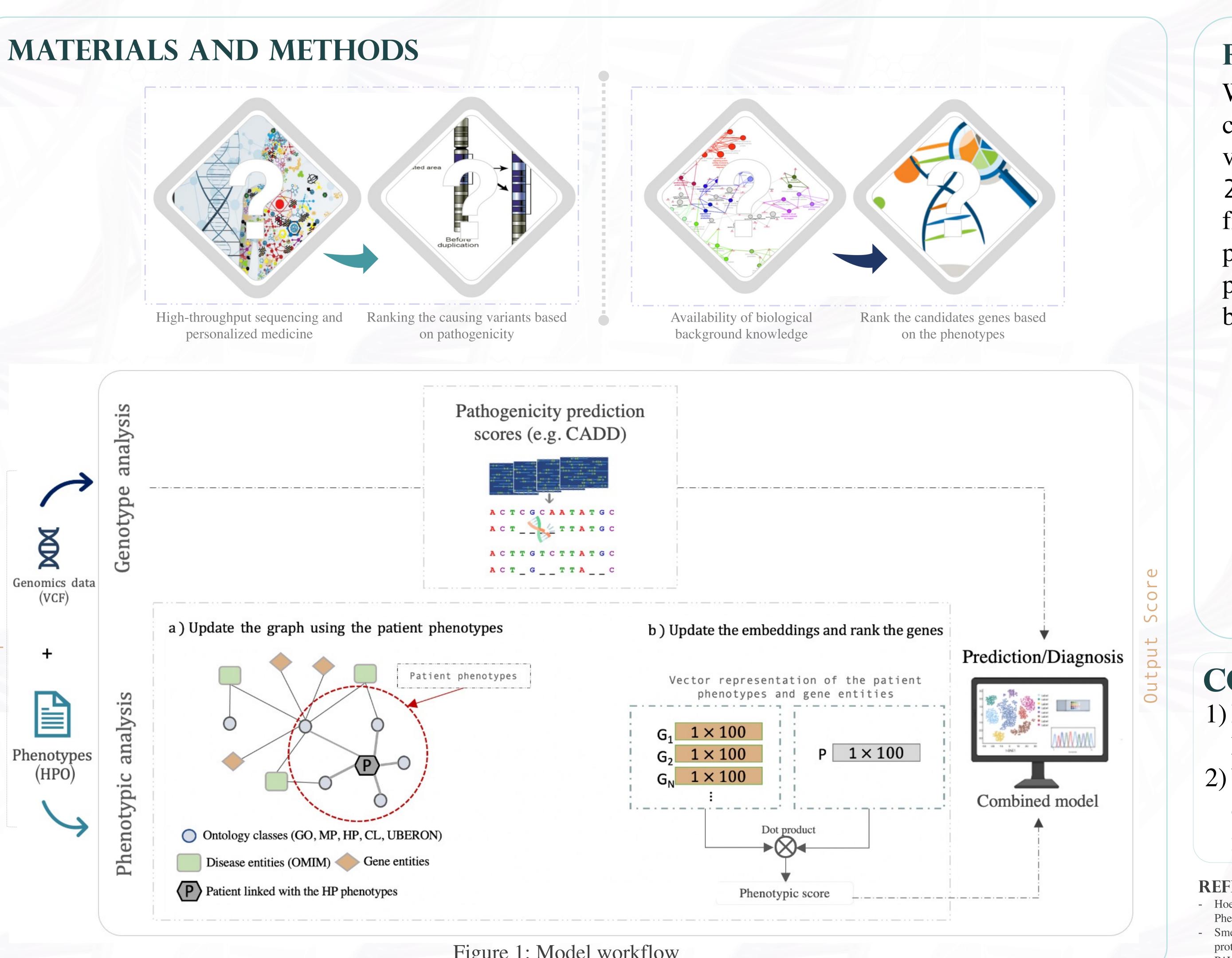
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BACKGROUND

- Understanding the molecular mechanisms underlying the set of abnormal phenotypes is important for the diagnosis, prevention, and development of therapies.
- We developed an AI model that uses background knowledge from human and model organisms to rank genes that are likely involved in a set of abnormal phenotypes.

RESEARCH QUESTIONS

- Can we design a deep learning model that learns to link gene functions and anatomical site of expression to the phenotypes resulting from a loss of gene function?
- Can we combine this AI-based prediction of candidate genes with pathogenicity predictions of variants to improve diagnostic yield when applied to whole whole genome exome or sequencing data?





AI-based Identification of Diagnostic Variants from Genotype and Phenotype Azza Althagafi^{1,2}, Robert Hoehndorf¹

Figure 1: Model workflow

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RESULTS

We combine our deep learning model for ranking candidate genes with pathogenicity predictions of variants and benchmark our method on a set of 259 pathogenic variants from Saudi Arabia. We find that our method significantly improves over pathogenicity prediction methods as well as other phenotype-based approaches that use less background knowledge.

| | | Top hit | Top@10 | Top@30 | Top@50 |
|----------------------------------|---------------------|----------------|----------------|----------------|----------------|
| Genotype-based prediction tools | CADD | 80 (0.3089) | 202 (0.7799) | 213 (0.8224) | 216 (0.834) |
| | MCAP | 24 (0.0927) | 174 (0.6718) | 174 (0.6718) | 174 (0.6718) |
| | SIFT | 92 (0.3552) | 179 (0.6911) | 179 (0.6911) | 179 (0.6911) |
| | PolyPhen2 | 152 (0.5869) | 180 (0.695) | 180 (0.695) | 180 (0.695) |
| Phenotype-based prediction tools | Exomiser_hiPHIVE | 29 (0.112) | 78 (0.3012) | 132 (0.5097) | 155 (0.5985) |
| | Exomiser_Phenix | 31 (0.1197) | 43 (0.166) | 71 (0.2741) | 126 (0.4865) |
| | Exomiser_PHIVE | 15 (0.0579) | 30 (0.1158) | 40 (0.1544) | 44 (0.1699) |
| | DeepPVP | 8 (0.0309) | 19 (0.0734) | 25 (0.0965) | 30 (0.1158) |
| DL2vec models | DL2vec_GO | 104 (0.4015) | 218 (0.8417) | 219 (0.8456) | 219 (0.8456) |
| | DL2vec_MP | 162 (0.6255) | 172 (0.6641) | 177 (0.6834) | 177 (0.6834) |
| | DL2vec_HP | 195 (0.7529) | 215 (0.8301) | 216 (0.834) | 216 (0.834) |
| | DL2vec_CL | 85 (0.3282) | 105 (0.4054) | 105 (0.4054) | 106 (0.4093) |
| | DL2vec_UBERON | 118 (0.4556) | 206 (0.7954) | 210 (0.8108) | 210 (0.8108) |
| | DL2vec_intersection | 79 (0.305) | 93 (0.3591) | 93 (0.3591) | 93 (0.3591) |
| | DL2vec_union | 95 (0.3668) | 206 (0.7954) | 210 (0.8108) | 210 (0.8108) |

Table 1: Benchmark results on genomes matched with clinical information

CONCLUSIONS

1) Deep learning biomedical methods over knowledge graphs improve variant interpretation. 2) We are able to relate gene functions and site of expression to phenotypes resulting from a loss of function.

REFERENCES:

- Hoehndorf, Robert, et al. "Semantic integration of physiology phenotypes with an application to the Cellular Phenotype Ontology." Bioinformatics 28.13 (2012): 1783-1789. - Smedley, Damian, et al. "Next-generation diagnostics and disease-gene discovery with the Exomiser." Nature protocols 10.12 (2015): 2004-2015.

- PAVS - Phenotype associated Variants in Saudi Arabia, http://pavs.phenomebrowser.net