**Bibliography**

**Why Deeplearning, Alphafold?**

**Advancement of AF for complex prediction and competitive binding to predict better binder.**

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