

# MINI-PROJECT VARIANT CALLING IN GENOMIC SEQUENCING DATA USING DEEP LEARNING

#### PRESENTED BY

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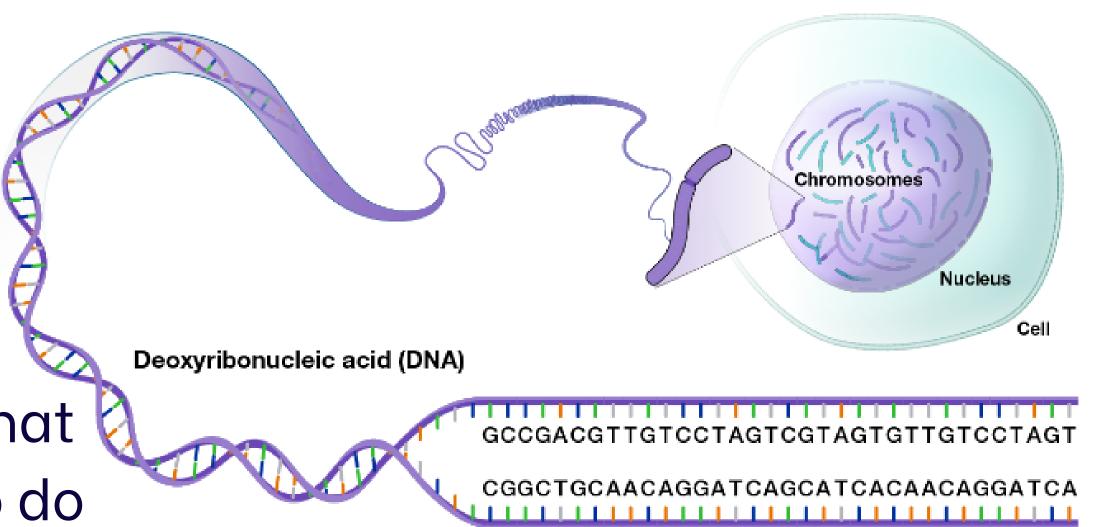
## HUMAN GENOME

 A genome is the complete set of DNA instructions found in every cell

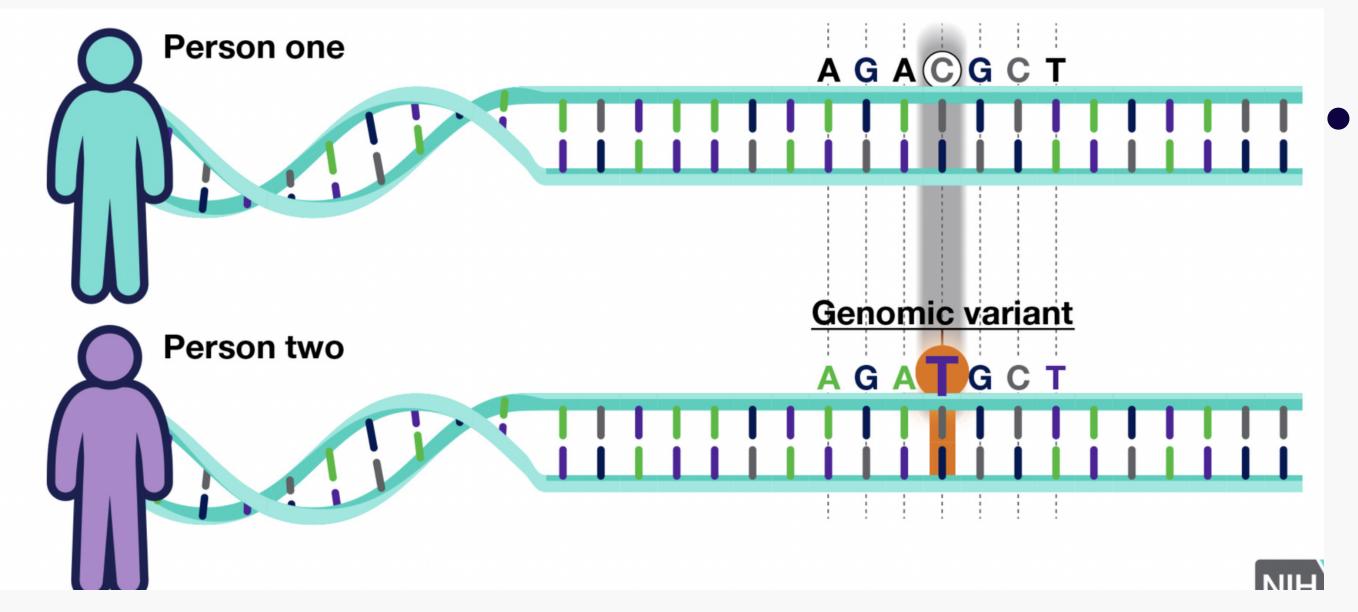
DNA is made of four different nucleotides:

adenine (A), thymine (T), cytosine (C) and quanine (G).

• The order of these letters (i.e., the DNA sequence) encodes the information that instructs each cell what to do and when to do it.



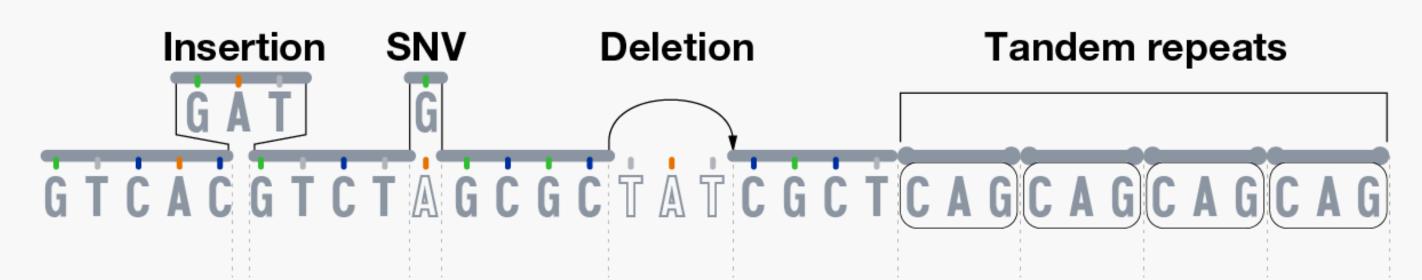
# **Human Genomic Variation**



 The vast majority of the DNA letters in peoples' genomes is identical, but a small fraction of those letters varies

• This genomic variation accounts for some of the differences among people, including important aspects of their health and susceptibility to diseases.

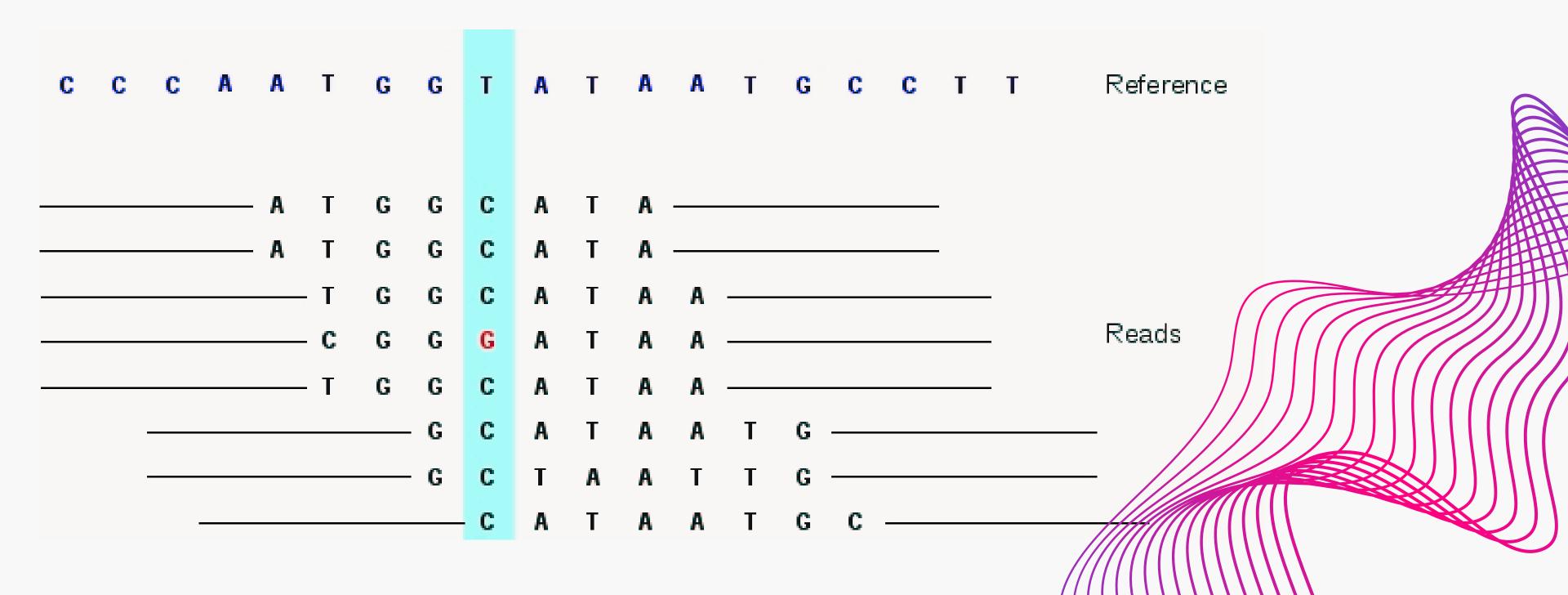
# Different Genomic Variations



- The smallest genomic variants are single-nucleotide variants (SNVs). Each SNV reflects a difference in a single nucleotide (or letter).
  - An insertion is a variation in which a specific nucleotide sequence is present in DNA
  - A deletion is a type of mutation that involves the loss of one or more nucleotides from a segment of DNA

# Variant Calling

- Align the sequences to a reference genome
- Identify where the aligned reads differ from the reference genome



### Limitations of traditional variant calling methods

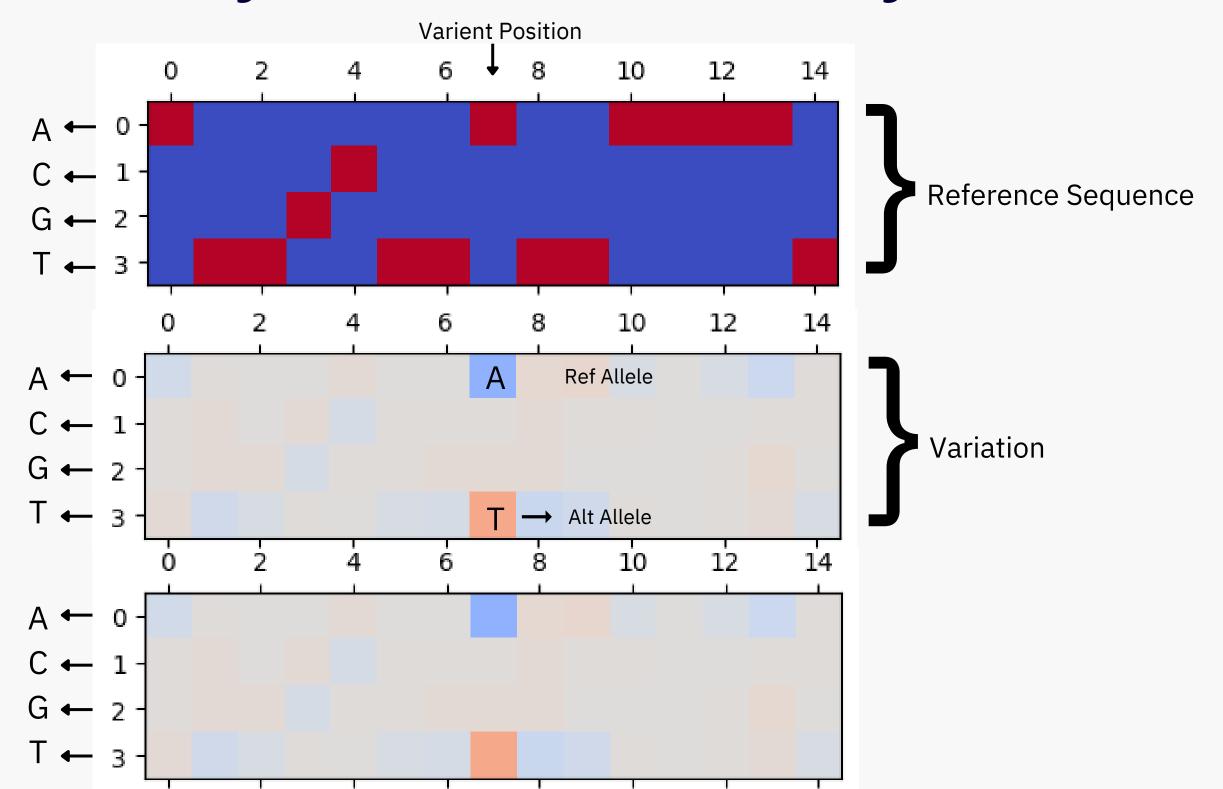
- Inaccurate for complex variants: Traditional methods struggle to identify and classify complex variants like indels and multiallelic variants.
- **Prone to sequencing errors:** Traditional methods are susceptible to false positive variant calls due to sequencing errors.
- Limited to specific variant types: Traditional methods are often tailored to specific variant types, limiting their applicability.
- Scalability issues with large datasets: Traditional methods can become inefficient when processing large volumes of sequencing data.

#### How the model overcome the issues

- Inaccurate for complex variants The model uses a deep learning approach that is able to learn complex patterns in the data.
- **Prone to sequencing errors** The model uses a variety of techniques to filter out sequencing errors, such as using quality scores and base calling consensus.
- Limited to specific variant types The model is able to handle a wide range of variant types, including SNPs, indels, and multiallelic variants.
- Scalability issues with large datasets The model is able to efficiently process large volumes of sequencing data.

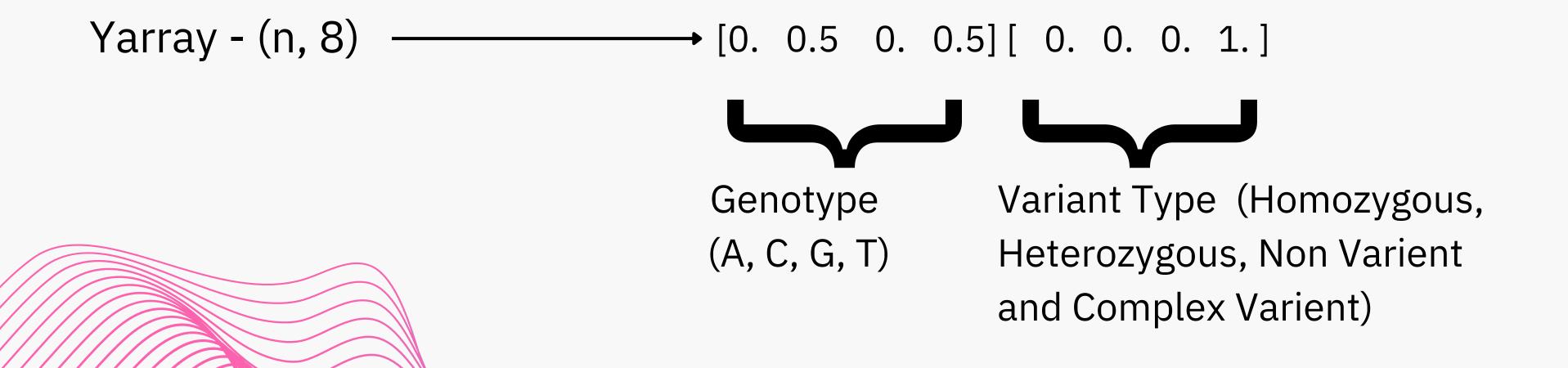
## How we identified the variants

• The alignments are converted to three 15 by 4 matrices for training the network and calling variants.



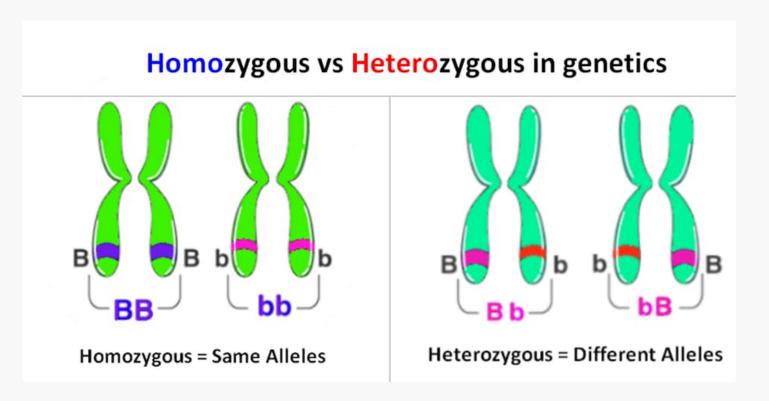
 Encode all alignments to a 15\*4\*3 tensor

- we train the neural network and classify the called variants into four categories: homozygous variant, heterozygous variant, non-variant or complex varient.
- It is also trained to predict the possible varient base



#### Homozygous

variant: A variant that is present on both copies of a chromosome in an individual.



#### Heterozygous

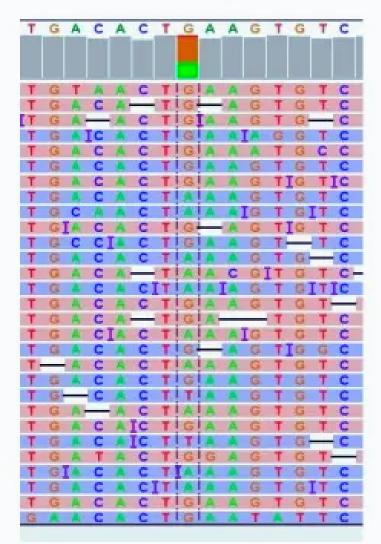
variant: A variant that is present on only one copy of a chromosome in an individual.

**Non-variant**: A variant that is not present in any of the individuals in the sample that was being sequenced.

**Complex variant**: A variant that is difficult to classify into one of the other categories.

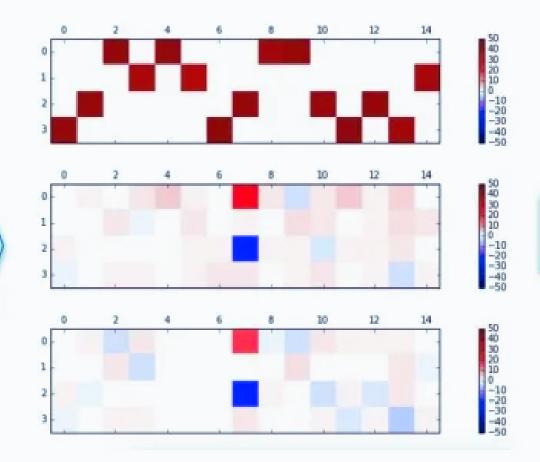
# Variant Calling Flowchart





Each candidate +/- 7 bp

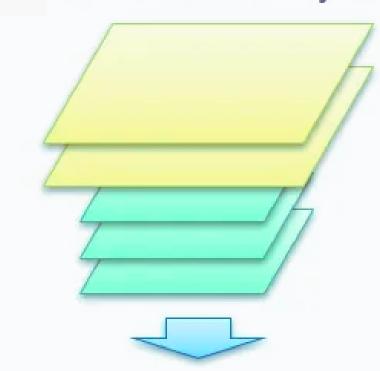




Encode all alignments to a 15 x 4 x 3 tensor

2 convolution layers

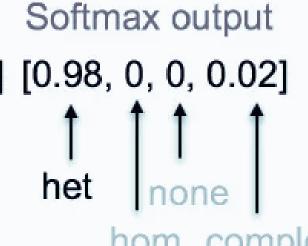
4 full connected layers



Genotype

[0.5, 0.0, 0.5, 0.0] [0.98, 0, 0, 0.02]







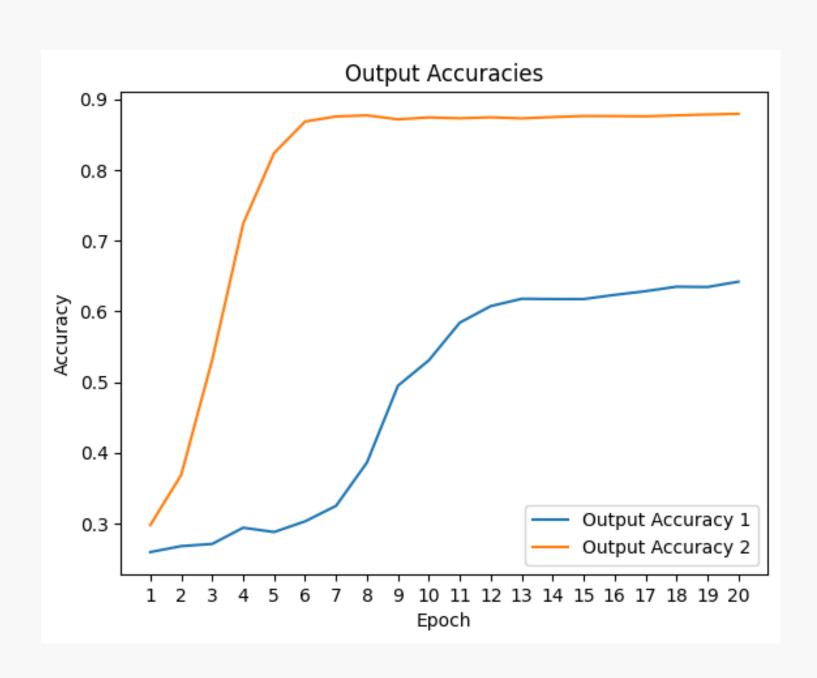




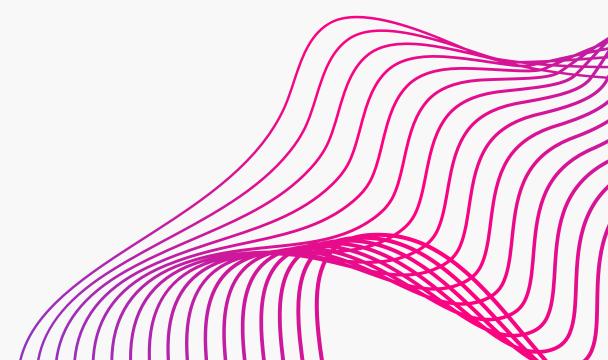




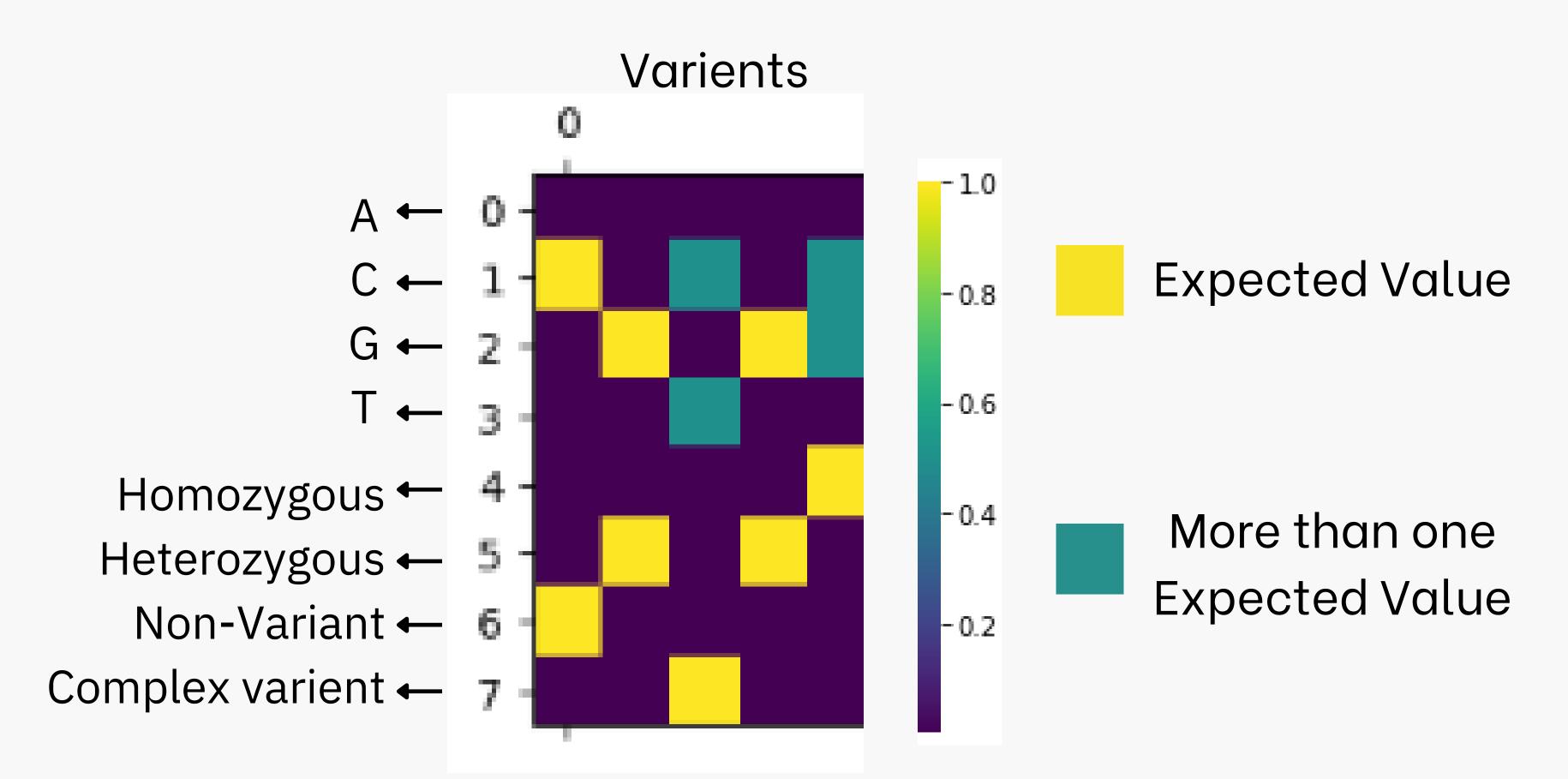
# Model Accuracy



Output 1 - Bases(A/C/G/T)
Output 2 - Varient Type
(hom/het/non/com)

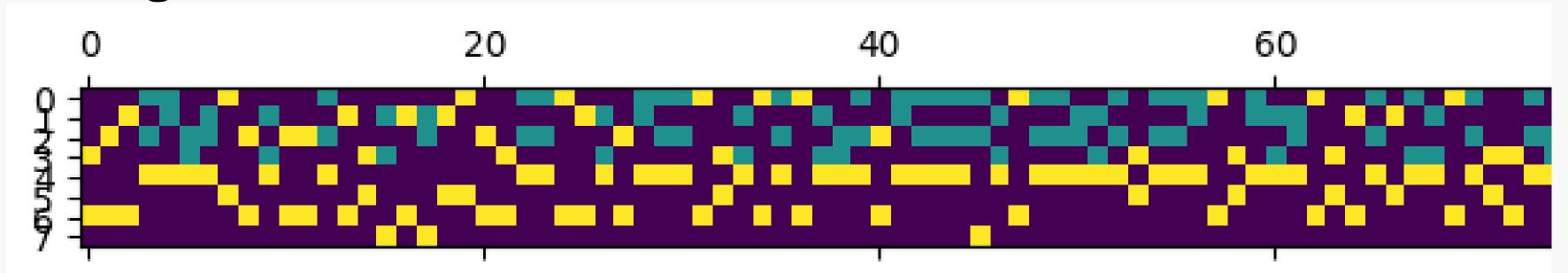


# Understanding the Predictions

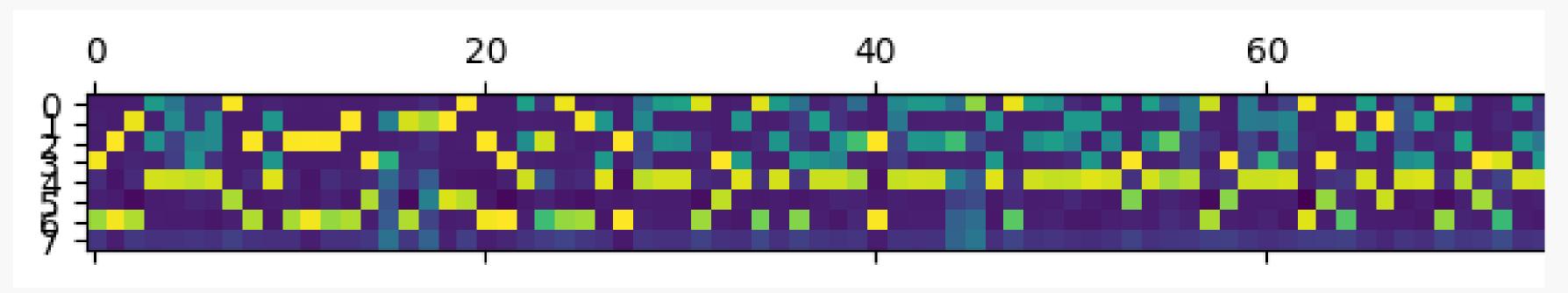


# Predictions

Original variant call



Predicted variant call



# Classification report

	precision	recall	f1-score	support
0	0.96	0.97	0.97	21809
1	0.96	0.99	0.97	9691
2	0.94	0.98	0.98	12609
3	0.90	0.90	0.54	3125
accuracy			0.95	47234
acro avg	0.94	0.87	0.89	47234
weighted	0.95	0.95	0.95	47234

# THANK YOU

